The Micro- and Macroeconomics of Unemployment and Job Protection

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Andreas Kettemann
from Germany

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Prof. Dr. Josef Zweimüller
Prof. Dr. Fabrizio Zilibotti

The Faculty of Business, Economics and Informatics of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

Zurich, 19.07.2017

Chairman of the Doctoral Board: Prof. Dr. Steven Ongena

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Preface

What I realize when thinking about my course of studies which started in 2007 and now ends a little less than ten years later is that things are hard to plan in advance. I came to St.Gallen in Switzerland to study business administration and ended up developing keen interest in economics. A short stint in economic research at the UBS Investment Bank motivated me to specialize in econometrics and finance. My bachelor thesis in econometrics, however, made me realize I am more of an economist than a statistician. This impression was reinforced by the six months I spent at the Swiss National Bank, where I made the final decision to obtain a PhD.

In Zurich, I started out at as a PhD student at the chair of Josef Zweimüller, while still having to take the master's and PhD courses. Since there was plenty of coursework to do and I was not expected to produce research output right away, this gave me valuable time to contemplate what I wanted to specialize in. At that time, the chair offered an ideal setting to this end. Josef's research interest comprises a wide range of fields: labor, international trade, growth and inequality, just to name the main areas. This created an inspiring atmosphere right from the beginning. That way, I was exposed to many different topics and approaches which, to my opinion, was crucial to become a good economist.

My previous work on econometrics qualified me most for the labor aspect of the chair and hence I spent my first months delving into the endless amount of micro data Josef has accumulated, especially the Austrian Social Security Data, which has kept me busy ever since. This is the reason why I sometimes have the impression I know more about Austria than about my country of origin, Germany, and my home country, Switzerland, taken together. This endless supply of data fascinated me. After a while, however, I more and more got the impression that approaching the data from a "theory-free" angle is also very difficult: Without the guidance of theory, I quickly got lost in the endless possible questions I could ask. This lead me to concentrate also on theoretical models of the labor market going forward.

To me, it only felt like being an economist once I managed to combine empirical and theoretical work. The different projects I was part of each required a different combination of approaches, tools and skills. While I am glad to see that all of the projects moved our frontier of knowledge a little bit further, I also hope to benefit from my versatility in my non-academic career, which is about to begin.

Along the way I briefly sketched, many people helped and supported me. First of all, I would like to thank my advisor, Josef Zweimüller, for making this whole endeavor possible. He created an inspiring and cozy research atmosphere in our late chair, encouraged me to work on interesting questions, and spent many hours discussing them with me. Thus, he was pivotal in my transition from a student to a researcher. I also would like to thank Fabrizio Zilibotti for agreeing to be my co-advisor. His ability to quickly immerse himself into a wide range of topics and give precise feedback truly fascinates me.

Two papers in this thesis are co-authored with Josef Zweimüller, François Fontaine, and Francis Kramarz. I am very grateful that they have agreed to collaborate with me and for the many things I learned from them along the way, especially as to how a research project is managed. A further project which does not show up in my dissertation is coauthored by Andreas I. Mueller. I am very indebted to him for inviting me to visit him at Columbia University, where I spent an unforgettable time.

I also want to thank Tobias Renkin, who started out around the same time as me and has become a close friend since then, Sandro Favre for interesting insights into (Swiss) history and the organization of barbecues, Philippe Ruh for introducing me to the mysteries of the Austrian Social Security Data, Andreas Haller for sharing the burden of teaching macroeconomics to graduate students, Andreas Steinhauer for demonstrating me how to connect theory and data, Christoph Winter for patiently investigating into my numerical problems, and Claudia Bernasconi, Beatrice Brunner, Christian Kiedaisch, Andreas Kohler, Andreas Kuhn, Harald Mayr, Aderonke Osikominu, and Stefan Staubli for making my time both instructive and memorable.

None of this would have been possible without the love and support of my family and friends. Many thanks go to my parents Michaela and Gerhard and my sister Laura for always giving me great independence while trusting and supporting my plans, my "second family" Martine, Jochen, and Theo for offering me a second home for meanwhile over twelve years, and, most importantly of all, my partner Nina. Your company, love, and encouragement during all the years enriched my life in so many ways and gave me the energy to make it to this point.

Zurich, February 2017

1 | Introduction

> "It often seems to me that's all detective work is, wiping out your false starts and beginning again."
>
> "Yes, it is very true, that. And it is just what some people will not do. They conceive a certain theory, and everything has to fit into that theory. If one little fact will not fit it, they throw it aside. But it is always the facts that will not fit in that are significant."
>
> — Agatha Christie, *Death on the Nile*

This thesis consists of three self-contained essays, which, while disparate in their emphasis, still have various aspects in common:

First, all three of them study transitions on the labor market, either focusing on the unemployed or the employed. It has long been understood that many aspects of labor markets, being subject to information frictions, cannot be studied adequately through the lens of a classical supply and demand framework. Thus, each paper relies on a search and matching environment to get a deeper understanding of the patterns we observe. The focus is then either put on the model's predictions on the macro level (chapter 2), trying to understand the evolution of labor market aggregates, or on the micro level (chapters 3 and 4), rationalizing observed behavior of individuals.

Second, at least two of the three essays (chapters 3 and 4) rely on quasi-experimental methods in order to identify a causal effect. Recent years have seen dramatic changes in what is expected of empirical work to be deemed credible. While previously studies posited empirical strategies that—while often being very complicated—were often ad-hoc and not very robust, empirical designs nowadays are expected to explicitly deal with identification, i.e. the way the data maps to the estimates through the empirical model. While the gold-standard is an experiment, quasi-experimental designs approximate this by looking at situations where real-world data can be treated *as if* generated by an experiment.

Third, all three essays draw on administrative data, most prominently the Austrian Social Security Database (Zweimüller et al. (2009)). While early studies mostly analyzed aggregate data, recent advance in computational power and in the availability of administrative and survey datasets have contributed to a shift toward the analysis of micro data. Since economists are eventually interested in how individuals react to incentives, individual-level data goes a long way toward understanding how economic mechanisms actually work. Here, these incentives are embodied in institutions such as unemployment insurance (chapters 2 and 3) and firing taxes (chapter 4) and interest lies in workers' reaction. This is even true if the nature of the analysis is more on the macro level (chapter 2), where knowledge of individual behavior contributes to a more credible microfoundation of aggregate relationships.

In the following, I will give a detailed overview of the individual chapters of this thesis:

Chapter 2: The Macroeconomics of Incomplete Unemployment Insurance Take-up

While the role of unemployment insurance (UI) for its recipients has been studied extensively, little research has been devoted to the question whether workers who are eligible for UI actually claim it. The most obvious economic argument would suggest that rational agents would always accept free money and hence that the take-up rate, the share of eligible workers claiming UI, is 100%.

Thus, it might be surprising that numerous empirical studies, drawing on different datasets from different countries, consistently measure take-up rates far below 100%. While this stylized fact is not explicitly addressed by most of the literature, this paper is devoted to exploring how accounting for incomplete UI take-up affects various predictions on the labor market. I do so by extending a Mortensen-Pissarides model (D. T. Mortensen and Pissarides (1994), Pissarides (1985), Pissarides (2000)) with endogenous search effort to allow for an endogenous UI take-up decision. UI take-up is modeled as a trade-off between a fixed cost to be paid upfront—we could think of this as administrative costs, information costs, but also as intrinsic aversion to the welfare state and stigma—and an uncertain length of benefit reception.

In a first step, I use a stochastic version of the model to explore the consequences for the cyclical behavior of the labor market. On the one hand, since workers expect longer unemployment spells in recessions, we predict a countercyclical take-up rate, which is consistent with the evidence. On the other hand, take-up interacts with search effort in an interesting way: Having claimed UI and thus receiving benefits lowers search effort. Thus, since relatively more workers receive benefits during recessions and vice versa during booms, variable take-up leads to additional procyclicality in aggregate search effort and hence also in the other labor market aggregates. Indeed, simulations suggest that the volatility of search effort is more than twofold compared to an economy where take-up is held constant, while the volatility of labor market tightness, unemployment, and vacancies increases by between 15 and 30%. I also find that the model produces dynamics of the take-up rate that closely match empirical observations. In addition to these broad conclusions, the model also has other interesting implications: First, while the unemployed who have not yet claimed UI can always revise their decision if conditions become worse, the reverse is not true. Thus, past adverse shocks can have long-lasting effects on unemployment as they increase the share of unemployed on benefits, even if current conditions are the same. Second, the model implies that the pool of workers on benefits differs at different stages of the business cycle. This might have important consequences for the optimal amount of UI benefits depending on the current state of the economy.

In a second step, I use a deterministic version of the model to investigate the consequences for the optimal time structure of UI payments. The baseline finding (Shavell and Weiss (1979), H. A. Hopenhayn and Nicolini (1997)) implies that UI benefits should be decreasing over time as search effort is unobserved leading to moral hazard. I show that accounting for a take-up decision leads to more backloading, possibly overturning the other effect. The intuition is the following: The government wants to minimize the cost of providing insurance subject to the constraint of providing a minimum level of expected utility to all unemployed. If workers differ in their job search ability, workers who are good at finding a job (high types) might already receive sufficient utility on their own, while the other workers (low types) need to be insured. To save costs, the government would want to exclude the high types, while only providing insurance to the low types. However, as types are not observed, the insurance contract has to be designed in such a way that only the low types select into it, while the high types do not have an incentive to claim. This is done by backloading the schedule: High types know their relative probability of being unemployed decreases over time. Thus, we can substitute payments early in the spell by payments later in a way that leaves the expected utility of low types unaffected but strictly decreases the expected utility of high types until they do not have an incentive to claim.

Chapter 3: Quasi-experimental Evidence on Take-up and the Value of Unemployment Insurance

This chapter is devoted to the same phenomenon as chapter 2, but looks at it from a different angle: While the previous chapter posited a specific behavioral model for the take-up decision and looked at aggregate implications, we are now taking a closer look at the actual factors underlying the take-up decision. We do so by using micro data and a quasi-experimental setting which allows us to interpret our estimates causally.

We exploit two policy discontinuities which do not coincide perfectly: On the hand, workers with at least three years of tenure at the time of the layoff are eligible for a severance payment of two monthly wages. On the other hand, workers who fulfill an experience criterion (at least three years of work experience within the preceding five years) are eligible for up to 30 weeks of UI benefits instead of the regular 20 weeks. Applying a regression discontinuity design (RDD), we find that the take-up rate jumps down at the former discontinuity, while it increases at the second. This is consistent with a benchmark job search model allowing for savings and endogenous take-up: If workers are liquidity constrained, higher assets will facilitate consumption smoothing even without claiming benefits. Extended benefits, in turn, increase the expected value of claiming, thus making it more attractive to take up.

Using our model, we show how our estimates can be used to compute bounds on a money metric of the value of unemployment insurance. First, the relative size of the reaction of take-up and search effort to eligibility for extended benefits can be used to estimate the shape of the distribution of take-up costs and the search cost function. Moreover, we show that there is a one-to-one mapping between the take-up probability and the difference in intertemporal utility between claimants and non-claimants. In order to convert this utility difference to monetary units, we normalize it by estimates of marginal utility obtained by combining the results of the first step and our point estimates.

Our results imply that the net benefit of claiming for claimants corresponds to roughly 2.5 monthly wages for the median individual. The benefit tends to be higher for low wage workers. For the non-claimants, our findings imply sizable costs of collecting benefits.

Chapter 4: Job Mobility and Creative Destruction: Flexicurity in the Land of Schumpeter

In this paper we study how a major policy change in Austria—the abolition of mandatory severance pay and its replacement by an occupational pensions scheme—affects job mobility. The new rules are valid for all workers who started their job as of January 1, 2003. There were two major changes: First, while under the old system only laid-off workers received a mandatory transfer, under the new system both laid-off workers and quitters are able to transfer their pension account to the new employer. Second, a discontinuous mandatory payment scheme, where the minimum severance payment amount is determined according to a step function of previous job tenure (in particular, there is no mandatory severance pay for tenure up to three years, while afterwards it increases to two monthly wages) is abolished in favor of a system where firms make monthly contributions to an account.

The policy change affects the incentives of workers who anticipate a future lay-off: Workers subject to the old system are expected to wait for a displacement in order to collect their severance pay. Under the new system, this incentive disappears: The regulation is neutral with respect to lay-offs and quits, and hence we expect to see workers more actively searching on the job in order to find higher paying jobs and limit the amount of time in unemployment. Importantly, note that the incentive only becomes relevant if workers consider a future lay-off sufficiently likely. Thus, in order to identify the reform's effect on job mobility, we have to focus on firms experiencing adverse shocks. We approximate adverse shocks by an observed mass layoff (or plant closure) and then look at worker mobility during the period preceding the event. We employ an RDD strategy—effectively comparing workers who entered a firm shortly before and after the reform—to isolate the reform effect from potential confounding factors.

We find sizable effects: Consider two workers, both having entered a firm three to four years before a mass layoff and both still employed after 12 months of tenure. Our baseline estimates imply that a worker subject to the new system is over 12.5 percentage points more likely to have left the employer after three years of tenure, which, from a base level of below 25%, corresponds to a relative increase of over 50%. Moreover, we show that the effect is mostly driven by workers directly moving to a new job and not by transitions into unemployment, which is consistent with theoretical predictions.

In order to rationalize the quantitative effects we document and in order to assess the aggregate implications, we build and estimate a job search and matching model featuring stochastic productivity shocks on the firm level, eligible and non-eligible workers, on-the-job search, and endogenous firm closure decisions. We find that the model can replicate the observed patterns in workers' behavior under reasonable parameter values, while also being able to match aggregate data. The model predicts a positive effect on productivity as workers reallocate more quickly from less to more productive firms. Moreover, unemployment is predicted to increase, as firms have a higher incentive to create jobs. While the effect on unemployment is moderate for the Austrian case, we show that the model can generate sizable responses if the pre-reform system is calibrated in a way resembling more a "Southern-European" case with high displacement costs.

2 The Macroeconomics of Incomplete Unemployment Insurance Take-up

2.1 Introduction

The take-up rate of unemployment insurance (UI), i.e. the share of those eligible actually claiming it, has only received limited attention in labor economics. Theoretical models of the labor market generally assume it is 100% – a natural assumption as it seems. Why should rational agents not accept free money? Given these considerations, it seems surprising that various empirical studies reviewed in the next section consistently estimate take-up rates far below 100%.

But why do the unemployed deliberately choose not to file for UI? Empirical evidence detailled in the next section suggests that claiming UI entails costs, while the benefits depend on the expected length of the unemployment spell. While the idea that the take-up decision is a trade-off between claiming costs and expected benefits is not new (see Currie (2004) for a survey of the literature and Anderson and Meyer (1997) for a simple partial equilibrium model of the take-up decision), these insights have not been studied systematically on the macro level. This despite the possibility that explaining incomplete UI take-up might not only be interesting in itself, but might also affect predictions elsewhere. Indeed, as demonstrated in this paper, endogenous take-up has important implications for the qualitative and quantitative predictions for the cyclical properties of the labor market and the optimal design of unemployment insurance.

In order to explore the implications of endogenous take-up on the macro level, I introduce an endogenous take-up decision in a stochastic version of the Mortensen-Pissarides (MP) search and matching model (D. T. Mortensen and Pissarides (1994), Pissarides (1985), Pissarides (2000)). I assume that filing for UI entails an upfront administrative cost, while the length of benefit reception and hence the payoff is uncertain. In line with the previous intuition, this means that the unemployed will only be willing to incur the claiming costs if they expect a sufficiently long duration of unemployment. Once the take-up costs have been borne, the individual stays on unemployment benefits for the rest of the spell. This abstracts from potentially recurring take-up costs (such as having to go to the caseworker's office) but corresponds to the intuition that most of the claiming costs are incurred at the beginning of the spell. An interesting implication of this setting is that the current pool of the registered unemployed in part reflects past states of the economy where the take-up decision was made.

In a first step, the model will be used to explore the take-up channel's implications for the cyclical behavior of the labor market. In equilibrium, job-finding rates are lower in recessions, which, according to the mechanism explained above, implies that individuals are more likely to claim. The model hence predicts a countercyclical take-up rate, which corresponds to the empirical evidence presented in the next section. But should we also be interested in take-up even if we did not concentrate on take-up directly? I argue that the take-up rate affects equilibrium in the labor market by interacting with search effort. I assume that, conditional on the take-up decision, unemployed individuals choose optimal search effort facing heterogeneous search costs. The consequences are twofold: On the one hand, those with low search costs who find a job relatively quickly find it less worthwhile to incur the cost of claiming unemployment insurance. Hence, there is selection of different types into registered and non-registered unemployment. On the other hand, conditional on the take-up decision, both subgroups face different incentives to find a job. Since the registered are partly insured against not finding a job, their search incentives are lower. Combining both aspects, the model predicts lower search effort and hence lower job-finding rates among the registered unemployed. However, this mechanism also implies that not the entire gap is due to monetary incentives, but also due to sorting of different types into both groups, whose characteristics affect search effort independently. Put differently, the interaction between search effort and take-up goes in both directions: Those who claim UI will have lower job-finding rates holding constant search costs. But across different types, those who find a job relatively quickly (those with lower search costs) are less likely to claim[1].

The interaction between search effort and take-up implies an amplification of fluctuations in aggregate search effort. More workers will refrain from claiming unemployment insurance and thus search at higher intensity if conditions are good. I calibrate the model to match the average job-finding rates of the registered and non-registered unemployed as well as the average take-up rate. Simulations implies that the volatility of search effort is more than twofold, while the volatility of labor market tightness, unemployment, and vacancies increases by between 15 and 30%. Simulations of historical data reveal that the model generates dynamics of labor market aggregates and the take-up rate that closely

[1]This realistic feature of the model would be preserved if we instead assumed heterogeneity in job-finding rates conditional on search effort, which would yield very similar dynamics. If we instead assumed heterogeneity in claiming costs, however, the claiming decision would be orthogonal to the search effort decision. This would mean that we would miss the sorting of different types into registered and non-registered unemployment, while we would attribute the entire gap in job-finding rates monetary incentives.

match empirical observations.

By proposing a mechanism that leads to amplification of fluctuations, the paper also adds to the literature initiated by Shimer (2005a), who demonstrated that the stochastic version of the standard MP model failed to account for the empirical volatility in the aggregates of the labor market if standard parameter choices are made – a fact that had already been noted by Andolfatto (1996). However, the model also has other important implications along the business cycle: First, the model has interesting predictions regarding path dependence. Past adverse shocks increase the share of unemployed on benefits and hence leads to lower exit rates even if current conditions are the same. Second, I will explore whether there are consequences for the optimal level of unemployment insurance along the business cycle. The calibrated model implies that the elasticity of search effort to unemployment insurance among the registered unemployed is higher during booms than during recessions, making a case for a countercyclical replacement rate. This hence mirrors findings by Landais, Michaillat, and Saez (2014), while the mechanism is different. While they emphasize general equilibrium effects going through the reaction of labor market tightness, this mechanism is absent here by construction. Instead, compositional shifts of registered workers induce different behavioral reactions at different points of the cycle.

In a second step, the steady-state version of the model is used to explore the take-up channel's implications for the optimal time structure of unemployment benefits. While according to a classical result in the literature, moral hazard implies that benefits should fall over time (Shavell and Weiss (1979), H. A. Hopenhayn and Nicolini (1997)), I demonstrate that endogenous take-up implies more backloading of the schedule, possibly overturning the effect of moral hazard. The intuition behind this result is the following: If workers have heterogeneous job-finding prospects, those with very good opportunities might not need to be insured in order to achieve the required level of discounted utility at the beginning of their spell. If worker types are not observable, the benefit schedule has to be designed in a way that gives sufficient utility to low types while having high types self-select into non-take-up. This is achieved by backloading, as low types value unemployment benefits in the future more than high types due to their higher probability of remaining unemployed. Numerical exercises suggest that the effect is potentially very sizable.

I begin in the next section by summarizing empirical evidence on take-up and search effort, followed by a discussion of related literature. In Section 2.4, I describe the theoretical model. Section 2.5 explores the quantitative and qualitative implications of the take-up channel along the business cycle, while Section 2.6 explains how take-up affects the optimal time-structure of unemployment benefits. Section 4.10 concludes.

2.2 Empirical Evidence on Take-up and Search Effort

Country	Source	Estimated take-up	Time period
Canada	Storer and van Audenrode (1995)	77%	1981 – 1986
United Kingdom	DWP[2] (2012)	49% - 84%	1997 – 2010
United States	Anderson and Meyer (1997)	24% - 50%	1979 – 1982
	Blank and Card (1991)	68% - 75%	1977 – 1987
	McCall (1995)	65%	1982 – 1991

Table 2.1: Overview of estimated take-up in existing studies

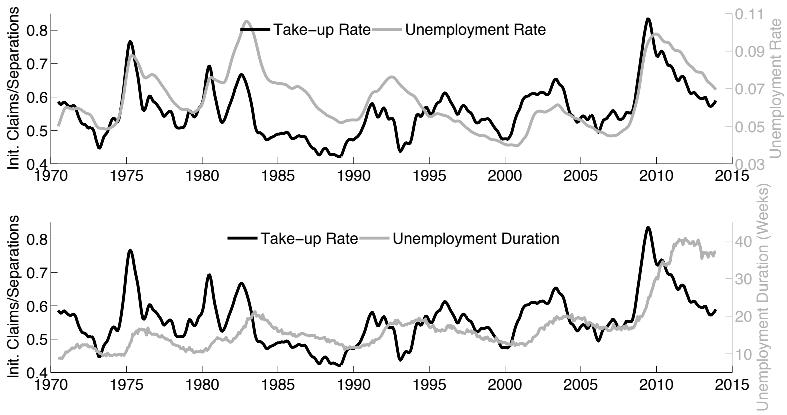


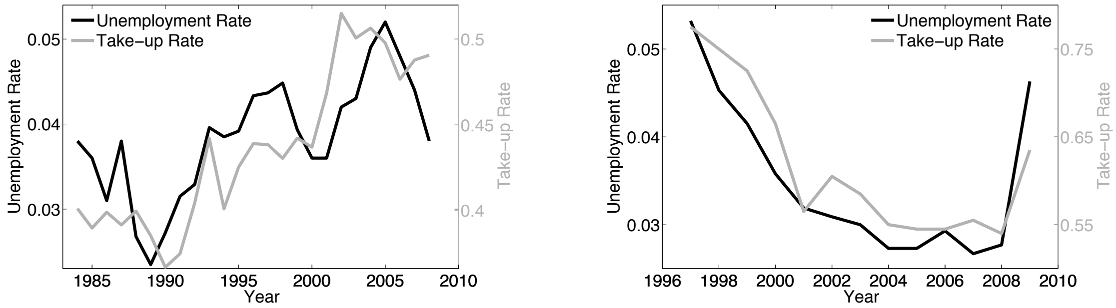
Figure 2.1: Take-up rate, unemployment rate, and unemployment duration in the US over time

Notes: The take-up rate is measured as the ratio of Initial Jobless Claims (constructed by the U.S. Department of Labor) and job separations, calculated from CPS data using the method detailled in Appendix A. The unemployment rate and unemployment duration are constructed by the BLS.

Various empirical studies, while differing in the point estimates[3], have consistently estimated UI take-up rates far below 100% (see Table 2.1 for an overview). Moreover, UI take-up is clearly countercyclical. This can be seen in Figure 2.1, plotting the take-up rate (measured as initial jobless claims divided by job separations) against the unemployment

[2]The British Department for Work and Pensions (DWP) is one of the few government agencies that regularly publish estimates of take-up rates.

[3]As has been pointed out by Blasco, Fontaine, and Margolis (2010), point estimates differ because of differences in the sampling scheme. Stock sampling oversamples long unemployment spells which have higher take-up rates, while flow sampling oversamples short spells. This distinction between stocks and flows will be important in this paper. I will call the flow measure take-up rate, i.e. the share of those entering unemployment claiming UI, while distinguishing this from the registration rate (stock measure), which is the share of all unemployed who have claimed UI some time in the past. Throughout, a registered unemployed is defined as an unemployed person who has claimed UI.



(a) Austria (b) UK

Figure 2.2: Take-up rate and unemployment rate in Austria and UK over time

Notes: For Austria, the take-up rate is constructed from Austrian Social Security Data and defined as the fraction of people between two jobs that ever claim UI during their nonemployment spell. The unemployment rate is constructed by the Austrian National Statistical Office. For the UK, the unemployment rate is constructed by the Office for National Statistics and reported as a yearly average. The take-up rate is constructed by the Department for Work and Pensions.

rate and unemployment duration in the US over time[4]. A similar observation can also be made for Austria (Figure 2.2a), using the data upon which the empirical section of this paper is based, and for the UK (Figure 2.2b), one of the few countries where official estimates of the take-up rate are published. This suggests that this stylized fact is also robust in an international comparison.

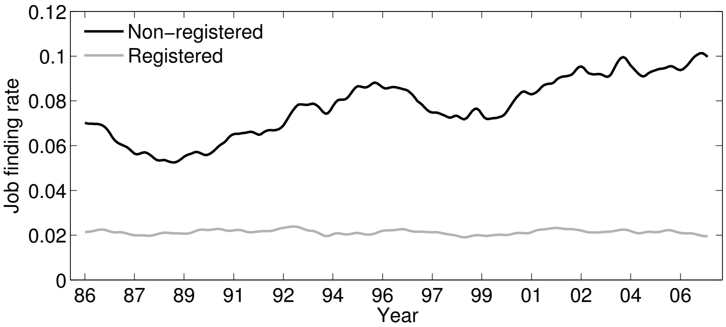


Figure 2.3: Job finding rates among registered and non-registered unemployed in Austria

Notes: Constructed from Austrian Social Security Data using all unemployed between 25 and 50 with unemployment spells below two years. I exclude employees recalled to their previous employer. The numbers are corrected for seasonality.

As mentioned in the previous section, the take-up decision will be modelled as a trade-off between upfront claiming costs and the expected unemployment duration. Is this a realistic characterization of the take-up decision? In a special CPS supplement administered in 2005, those with self-reported eligibility who did not claim UI were asked for their

[4]It has been noted by Hobijn and Şahin (2011) that initial jobless claims overstate layoffs if the take-up rate is countercyclical.

Reasons for not applying for UI	Number in thousands	Percent
Attitude/understanding/barrier to UI benefits	778	37.00
Do not need money/do not want the hassle	220	10.40
Negative attitude about UI	78	3.74
Do not know about UI/how to file	212	10.19
Barrier to filing (e.g. language, transportation)	52	2.49
Told not eligible	175	8.32
Plan to file soon	42	2.08
Job expected/became employed	594	28.27
Not looking for a job	231	11.02
Other reasons/don't know	496	23.70
Total	4368	100.00

Table 2.2: Reason for not applying for UI benefits in current unemployment spell, job losers and leavers eligible for UI (self-reported) (Vroman (2009), Table 4)

Notes: The figures represent population estimates of responses to the following question from a special CPS supplement administered in January, May, July, and November 2005: "What is the main reason ... has not applied for unemployment compensation since ... last job?" The population estimates are obtained using the CPS weights.

main reason (Table 2.2). About two thirds of all responses are accounted for by the categories "Attitude/understanding/barrier to UI benefits" (37%) and "Job expected/became employed" (28%). The importance of the former category demonstrates that claiming UI is costly and that these costs have to be incurred upfront. The latter category, in turn, implies that workers take their labor market prospects into account when deciding whether to claim unemployment insurance. The results hence suggest that a trade-off between upfront claiming costs and expected benefit duration is a good description of the actual mechanism at work.

Theory also predicts higher search effort and hence higher job-finding rates among non-registered unemployed. Indeed, Figure 2.3, where I plot the average weekly job-finding rates for the registered and non-registered unemployed in Austria over time, demonstrates that the non-registered unemployed are around four times more likely than the registered to find a job within one week.

To get a rough idea of how the interaction of search effort and take-up might be important along the business cycle, the following accounting exercise is instructive: Assume the aggregate job-finding rate, f_t, evolves over time according to

$$f_t = s_t f_t^1 + (1 - s_t) f_t^0,$$

where f_t^1 and f_t^0 denote the job-finding rates among the registered and non-registered unemployed, respectively. Assume that $e \equiv f_t^1/f_t^0$ is constant over time, yielding

$$f_t = (s_t + (1 - s_t)e)f_t^0.$$

Assuming a value for e and given data on f_t and s_t, we can back out an implied value of f_t^0. To see how much variable take-up potentially contributes to the aggregate movement of the job-finding rate, we can calculate the counterfactual job-finding rate if take-up is held constant,

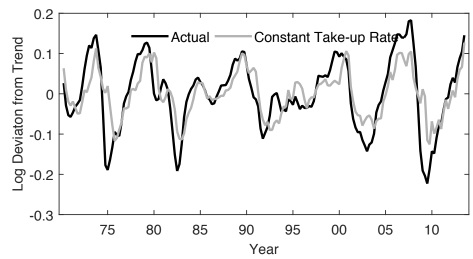
$$\tilde{f}_t = (\bar{s} + (1 - \bar{s})e)f_t^0,$$

where $\bar{s}$ denotes the average take-up rate, as well as the counterfactual job-finding rate if the conditional job-finding rates are held constant, given by

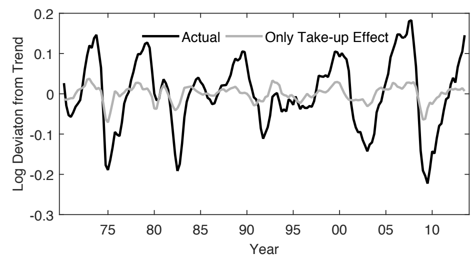
$$\tilde{\tilde{f}}_t = (s_t + (1 - s_t)e)\bar{f}^0,$$

where $\bar{f}^0$ is the average job-finding rate among the non-registered.

In Figure 2.4, we plot the results for the US, choosing e so that the average weekly job-finding rate among the non-registered is around four times as large as among the registered. The results suggest that the take-up effect is important especially at the onset of recessions. For instance, the simple calculation implies that the fall in the job-finding rate during the Great Recession was around twice as large as compared to a situation where the fraction of the unemployed claiming unemployment insurance remained constant.



(a) Actual vs. constant take-up counterfactual



(b) Actual vs. constant conditional job-finding rate counterfactual

Figure 2.4: Job-finding rate in the US, actual vs. counterfactuals

Notes: The black lines correspond to the monthly job-finding rate, constructed by Shimer (2005a) and based on unemployment data constructed by the BLS based on the CPS. The gray line in panel (a) corresponds to the counterfactual job-finding rate if the take-up rate is fixed at its average level, while the gray line in panel (b) corresponds to the counterfactual job-finding rate if the conditional job-finding rates are kept constant and only the take-up rate varies. Details on the construction are in the main text. All numbers are quarterly averages of monthly series and reported in logs as deviations from an HP trend with smoothing parameter 1,600.

While this back-of-the-envelope calculation indicates that accounting for take-up might be quantitatively important, there are still too many simplifications to draw a definite conclusion: On the one hand, differential selection of different types into registered and non-registered unemployment, as explained above, might explain part of the gap in average job-finding rates between the registered and non-registered unemployed. This implies that the marginal type who switches from claiming to not claiming (or vice versa) at a given point in time might increase his search effort by less since she only reacts to the monetary incentive while heterogeneity is kept constant. On the other hand, we have approximated the share of unemployed on benefits (a stock measure), by the take-up rate (a flow measure), which is not entirely correct.

Hence, a model is needed which takes care of these issues. A model will also enable us to gain further intuition of how search effort and take-up interact, as well as to draw normative conclusions.

2.3 Related Literature

Previous work on UI take-up primarily focused on empirical investigations of its determinants. These are surveyed in Currie (2004) and Hernanz, Malherbet, and Pellizzari (2004), notable examples are Blank and Card (1991), McCall (1995) and Anderson and Meyer (1997), all concluding UI generosity is a significant determinant of take-up, as well as Burtless (1983), among the first to document the stylized fact and exploring possible explanations. Budd and McCall (1997) analyze the role of unions in the take-up decision, finding that eligible blue-collar workers laid-off from union jobs were 23% more likely to receive benefits. The authors interpret these findings as suggesting that unions help workers to exercise their rights, i.e. reduced claiming costs. Petrongolo (2009) empirically analyzes a mechanism similar to the one considered here, showing that a UK JSA reform increasing job search requirements significantly increased the share of non-claimants. Kroft (2008), on the other hand, investigates the implications of a variable take-up rate for optimal unemployment insurance in a static environment. He finds that the effect depends on whether there are social spillovers, i.e. whether take-up costs are lower in times of high take-up. The presence of take-up decreases its level if no social spillovers are present, while its level is increased in the opposite case.

In a recent working paper, Hertel-Fernandez and Wenger (2013) describe an experiment where randomly selected unemployed were provided accurate information about UI eligibility requirements. Contrary to expectation, treated individuals actually had lower participation. The authors interpret the finding as a consequence of uncertainty about actual take-up costs. Ebenstein and Stange (2010) exploit cross-state variation in the introduction of phone- and internet-based claiming but do not find significant effects on take-up, suggesting physical barriers alone do not explain non-take-up. On the contrary, though not connected to UI, Kopczuk and Pop-Eleches (2007) show that the introduction of electronic filing for Earned Income Tax Credit significantly increased participation. In a field experiment, randomly sending different reminders to non-claimants of EITC benefits, Bhargava and Manoli (2015) find that claiming was very responsive to treatments that attempted to simplify information. By contrast, treatments that attempted to reduce perceived costs connected to application, stigma, or audit did not have a significant effect. In sum, while the numbers in Table 2.2 point to a significant role for take-up costs, the cited studies remain inconclusive as to their exact composition. While this is an important question for policy makers, the exact composition of take-up costs will not be important for the mechanism presented here.

Only recently have there been attempts to come up with structural models to explain the take-up process in more detail. One of them is Blasco and Fontaine (2012), who incorporate a take-up decision in a detailed partial equilibrium job search model and then use structural estimation to identify the parameters (Petrongolo (2009) also applied a partial equilibrium search model to demonstrate the effect of higher job search requirements). Their results suggest that transaction costs in the claiming process are substantial. Take-up of welfare programs, by contrast, was already analyzed by Moffitt (1983), who emphasizes the role of stigma. However, a critical point about stigma as an explanation for non-take-up is that take-up of means-tested programs is not lower whereas they should be more stigmatic (see Currie (2004) for more on this).

There are only two models that introduce UI take-up in a general equilibrium setting I am aware of. One is Auray, Fuller, and Lkhagvasuren (2013). Their setting is only relevant for a system where firms are experience rated. This means that firms pay higher payroll taxes if more of their previous employees collected benefits. Since firms thus prefer workers not taking up UI, these will enjoy higher job arrival rates and workers will select endogenously into registered and non-registered unemployment. While their model works well to predict long-term averages in the data, their mechanism is quite different from the one presented here. Closest to my work is Chodorow-Reich and Karabarbounis (2014). They introduce a take-up decision into a DSGE model with matching frictions and a representative household in order to calculate the cyclicality of the opportunity cost of employment. However, their strategy differs from mine in that they model take-up as a static decision problem: The representative household decides how many of its members to allocate to UI, trading off take-up costs that are increasing in the number of claimants against take-up value, which depends on the marginal value of consumption and is hence cyclical. By contrast, I model take-up as a forward looking decision that emphasizes the aforementioned trade-off between an upfront claiming cost and the expected length of unemployment, which I consider key in understanding this phenomenon given the findings in Table 2.2.

2.4 The Model

2.4.1 Environment

The model is in discrete time. I assume log productivity p follows a Markov process represented by the conditional c.d.f. $G(p'|p)$ and specified as (throughout, primes denote next-period values)

$$p' = \rho p + \varepsilon',$$

where p is standardized to have average 0 and ε denotes productivity innovations.

To the extent that firms and workers incur search costs before forming a match, there is a positive match surplus that has to be shared according to a wage setting rule. Theoretically, any rule that guarantees that the wage stays within the bargaining range is compatible with the model assumptions. I depart from the standard MP framework in following Blanchard and Galí (2010) and Michaillat (2012) in assuming that wages satisfy

$$w(p) = w_0 \exp((1 - \gamma)p),$$

which can be seen as a reduced-form way of representing sticky wages, where $0 \leq \gamma \leq 1$ denotes the extent of wage rigidity. For $\gamma = 0$ we get a perfectly elastic wage, while $\gamma = 1$ corresponds to the special case of constant wages analyzed by Hall (2005). As long as p is bounden from below and from above, parameters can always be chosen such that the wage is guaranteed to stay within the bargaining range. In Section 2.5.3, I demonstrate that the main conclusions for the behavior along the business cycle are unchanged – if anything, the effect of take-up on cyclicality becomes larger – if we assume Nash bargaining instead.

As noted by Shimer (2005a), wage stickiness is a way of inducing sufficient volatility in the stochastic DMP model. Hence, by choosing a sufficiently high γ, we could already match the observed volatility of labor market aggregates. By contrast, I will use γ to generate sufficient baseline volatility, which is then amplified by the take-up channel so as to close the gap to the data. A way of assessing amplification due to take-up would be to compare the values of γ with and without take-up needed in order to generate enough volatility in the model. Moreover, setting $\gamma > 0$ also reflects the fact that research up to this date has suggested many sensible remedies for the Shimer puzzle which should be at work beside the take-up channel.

The matching technology maps the aggregate unemployment rate u, aggregate vacancy rate v and aggregate search effort e to the number of matches formed m, according to

$$m = m(e \cdot u, v),$$

where $m(\cdot, \cdot)$ is increasing in both arguments and features constant returns to scale. Defining the job-market tightness as

$$\theta \equiv \frac{v}{e \cdot u},$$

the probability that a vacancy is filled can be written

$$\frac{m(e \cdot u, v)}{v} = m\left(\frac{e \cdot u}{v}, 1\right) \equiv q\left(\theta\right),$$

where $q'(\theta) < 0$, while the probability that unemployed person i with search effort e_i finds a job is given by

$$e_i \frac{m(e \cdot u, v)}{e \cdot u} = e_i m\left(1, \frac{v}{e \cdot u}\right) = e_i \theta q\left(\theta\right) \equiv e_i f\left(\theta\right),$$

where $f'(\theta) > 0$.

Following general practice, I assume that m is Cobb-Douglas,

$$m = m_0 (e \cdot u)^{\alpha} v^{1-\alpha},$$

implying $q(\theta) = m_0 \theta^{-\alpha}$ and $f(\theta) = m_0 \theta^{1-\alpha}$.

2.4.2 Firms

Firms produce with a linear production technology. Hence the firm size is indeterminate and we can assume that one firm consists of one job, which is either occupied and produces p, or vacant and costs c. A separation occurs with exogenous probability λ. In these respects the labor demand side of the economy is standard and follows Pissarides (2000).

The value of a job and of a vacancy then satisfy, respectively:

$$J(p) = \exp(p) - w(p) + \delta\left[(1-\lambda)\mathbb{E}_p J(p') + \lambda \mathbb{E}_p V(p')\right] \tag{2.1}$$

$$V(p) = -c + \delta\left[q\left(\theta(p)\right)\mathbb{E}_p J(p') + (1 - q\left(\theta(p)\right))\mathbb{E}_p V(p')\right] \tag{2.2}$$

If a job is filled, it produces $\exp(p)$ and costs $w(p)$ currently. With probability λ the job is dissolved, while it persists with probability $1-\lambda$. A vacancy costs c and is filled with probability $q(\theta(p))$ while with opposite probability it remains vacant. Using the free-entry condition $V(p) = 0$ in (2.2), we find

$$\mathbb{E}_p J(p') = \frac{c}{\delta q(\theta(p))}, \tag{2.3}$$

which can be substituted in (2.1) to yield

$$J(p) = \exp(p) - w(p) + (1 - \lambda)\frac{c}{q(\theta(p))}.$$

Taking expectations, updating one period and replacing $\mathbb{E}_p J(p')$ in (2.3), we arrive at a rational expectations functional equation

$$\frac{c}{\delta q\left(\theta(p)\right)} = \mathbb{E}_p \left\{ \exp(p') - w(p') + (1 - \lambda)\frac{c}{q\left(\theta(p')\right)} \right\}, \tag{2.4}$$

requiring that firms create vacancies until expected hiring costs equal expected discounted profits. Given the assumed functional form for $w(p)$, this equation pins down a policy function $\theta(p)$ and can easily be solved numerically.

Importantly, $\theta(p) \equiv v(p, e, u)/(eu)$ is invariant to changes in e and u, meaning that firms vary vacancies one-to-one with aggregate search effort and unemployment. The solution $\theta(p)$ holds irrespective of worker behavior, while it feeds back into firm behavior through bargaining in the standard model. In the present framework, the simple reduced-form specification of wages leads to a block-recursive model, so that we can solve for the firm policy function $\theta(p)$ and then determine worker behavior taking $\theta(p)$ as given.

2.4.3 Workers

Workers are assumed to be risk-neutral, abstracting from savings motives. In contrast to the usual strategy, where we assume that workers receive unemployment benefits automatically once they become unemployed, I now take the aforementioned stylized facts into account by assuming that UI has to be claimed and that claiming is costly. In particular, the unemployed incur upfront administrative costs ψ in order to qualify for unemployment insurance benefits z during every period of the remaining unemployment spell, including the current. Note that this induces an asymmetry: If already registered, claiming costs are sunk and there is never an incentive to leave registered unemployment except by finding a job. On the other hand, it might well happen that claiming occurs after a period of non-registered unemployment.

By modelling take-up costs as a one-time upfront payment, I abstract from potentially recurring costs, such as those of having to stick to the rules or of the psychological hurdle of having to go to the UI office. While this is clearly a simplification, it corresponds to the intuition that most of the hazzle connected to claiming UI benefits occurs at the beginning of a spell: Acquiring information about the system, overcoming one's intrinsic aversion of receiving benefits, putting together all material needed for the claim, and so on. Moreover, recurring take-up costs will in part be reflected in the model if we interpret unemployment benefits as net of recurring take-up costs.

Conditional on the registration status, the unemployed choose search effort optimally, facing strictly convex search costs $c(e_i) = \omega_i(1+\kappa)^{-1}e_i^{1+\kappa}$, where $\kappa > 0$ and $\omega_i > 0$ is heterogeneous and constant over time. I could also have assumed heterogeneity of claiming costs, but this way I can account for the conjecture that registered and non-registered unemployed are also different in other dimensions. This means that the model will generate differences in job-finding rates between the two groups not only because of different monetary incentives, but also because both groups differ ex-ante in characteristics that affect search effort independently of the take-up decision.

Denote by $T_i(p)$ and $N_i(p)$ the values of a registered and non-registered unemployed with ω_i, respectively. If not yet registered, individual i files for unemployment insurance if $T_i(p) - \psi \geq N_i(p)$. Let $U_i(p) \equiv \max\{T_i(p) - \psi, N_i(p)\}$. Conditional on not (yet) having claimed for unemployment insurance, individual i then solves

$$N_i(p) = \max_{e_i \geq 0}\left\{\ell - \frac{\omega_i}{1+\kappa}e_i^{1+\kappa} + \delta\left[e_i f(\theta(p))\mathbb{E}_p W_i(p') + (1 - e_i f(\theta(p))\mathbb{E}_p U_i(p')\right]\right\}. \quad (2.5)$$

If not yet registered, individual i currently only earns the value of leisure ℓ minus the search cost. In the subsequent period, a job is found with probability $e_i f(\theta(p))$, while the individual remains unemployed with opposite probability. The continuation value is then given by $\max\{T_i(p) - \psi, N_i(p)\}$, since i might change into registered unemployment for some realizations of p'.

I conjecture that $T_i(p) > N_i(p)$ for all p and ω_i, so that registered unemployed never have an incentive to switch back into non-registered unemployment. This (rather intuitive) statement will be shown formally in the next section. Conditional on having already registered, individual i then solves

$$T_i(p) = \max_{e_i \geq 0}\left\{\ell + z - \frac{\omega_i}{1+\kappa}e_i^{1+\kappa} + \delta\left[e_i f(\theta(p))\mathbb{E}_p W_i(p') + (1 - e_i f(\theta(p))\mathbb{E}_p T_i(p')\right]\right\}. \quad (2.6)$$

If already registered, i receives benefits z in addition to the value of leisure. If no job is found, i remains registered for every realization of future productivity, earning $T_i(p')$. If employed, individual i earns value

$$W_i(p) = w(p) + \delta \left[\lambda \mathbb{E}_p U_i(p') + (1-\lambda)\mathbb{E}_p W_i(p')\right]. \tag{2.7}$$

If employed, i currently earns $w(p)$ while facing the choice of registering if the match is dissolved.

2.4.4 Equilibrium and Aggregate Dynamics

An equilibrium in this economy describes vacancy creation decisions by firms for different levels of productivity, and search effort and take-up decisions by the unemployed for different levels of productivity and search costs. The equilibrium conditions in this economy are summarized in the following definition:

Definition 2.1. *An equilibrium is given by functions* $\{\theta(p), e_i(p,0), e_i(p,1), k_i(p)\}$ *and values* $\{N_i(p), T_i(p), W_i(p)\}$ *such that*

1. *labor market tightness* $\theta(p)$ *solves the recursive equation (2.4);*
2. *search effort if not registered* $e_i(p,0)$ *solves (2.5) given* $\{N_i(p), T_i(p), W_i(p)\}$ *for all* p *and* i*;*
3. *search effort if registered* $e_i(p,1)$ *solves (2.6) given* $\{N_i(p), T_i(p), W_i(p)\}$ *for all* p *and* i*;*
4. *the take-up decision is given by* $k_i(p) = \mathbf{1}\left[T_i(p) - \psi \geq N_i(p)\right]$ *for all* p *and* i *and;*
5. *values* $\{N_i(p), T_i(p), W_i(p)\}$ *solve recursive equations (2.5) - (2.7).*

In more intuitive words, we require that (1) firms create vacancies until they make zero profit in expectation, (2) and (3) the unemployed not registered and registered choose search effort until marginal search costs equal marginal search return, (4) non-registered unemployed choose to register if their discounted utility when registered net of claiming costs exceeds discounted utility when not registered, and (5) agents have rational expectations, i.e. present discounted utility takes future optimal decisions into account.

To prove existence of this equilibrium, I proceed in two steps. As a first step, I prove that the firm's policy function $\theta(p)$ pinned down by equation (2.4) exists and is unique. This is established in Proposition 2.1. Given the block-recursive nature of the model, I can then take this result as given and prove the existence and uniqueness on the worker side.

Proposition 2.1. *Assume that $p \in [\underline{p}, \overline{p}]$. Then, the policy function $\theta(p)$ defined by condition (2.4) exists and is unique. In addition, as long as instantaneous profits* $\exp(p) - w(p)$ *are positive, $\theta(p)$ is strictly increasing in p.*

Proof. See appendix. □

Under assumptions that guarantee that job-finding rates do not become too high, it can be shown that the equilibrium defined in Definition 4.1 exists and is unique:

Proposition 2.2. *Assume that $p \in [\underline{p}, \overline{p}]$ and that ω_i is bounded below by some $\underline{\omega} > 0$ so that* $\max\{e_i f(\theta(p))\} \leq 1 - \lambda$. *Then, the equilibrium defined in Definition 4.1 exists and is unique.*

Proof. See appendix. □

Up to now, I used the assumption that $T_i(p) > N_i(p)$ for all p and ω_i to rule out any incentive to switch back to non-registered unemployment. The following result justifies this:

Lemma 1. *If $z > 0$, then $T_i(p) > N_i(p)$ for all p and ω_i.*

Proof. Define $\tilde{N}_i(p, e_i)$ and $\tilde{T}_i(p, e_i)$ as the value of non-registered and registered unemployment for given e_i. We have $N_i(p) = \tilde{N}_i(p, e_i^N(p))$ and $T_i(p) = \tilde{T}_i(p, e_i^T(p))$, where $e_i^N = \arg\max_{e_i \geq 0} \tilde{N}_i(p, e_i)$ and $e_i^T = \arg\max_{e_i \geq 0} \tilde{T}_i(p, e_i)$. Then

$$N_i(p) = \tilde{N}_i(p, e_i^N(p)) < \tilde{T}_i(p, e_i^N(p)) \leq \tilde{T}_i(p, e_i^T(p)) = T_i(p),$$

where the first inequality follows since i is given a positive payment z currently and possibly in the future, while transition rates are unchanged. □

Denote by $s_i \in \{0, 1\}$ whether individual i is registered. Moreover, define $k_i(p) \in \{0, 1\}$ as the take-up decision given p. In the next subsection, I will prove that the unemployed will follow a cutoff rule under mild conditions, i.e. for every worker there is productivity level $\bar{p}_i$ such that $k_i(p) = \mathbf{1}[p \leq \bar{p}_i]$. Note that $k_i(p)$ differs from s_i in that s_i is 1 if i has registered in the past, while $k_i(p)$ is 1 if i would want to register now. Once registered, person i can only exit registered unemployment by finding a job. The policy function $k_i(p)$ answers the question: If I were unemployed and not yet registered, would I want to claim UI given my search costs and current productivity? $k_i(p)$ can be regarded as a flow measure of take-up. Another question we could ask is: If I observe an unemployed worker with search costs ω_i, how likely is he to be registered? This is described by a stock measure of take-up, given by the probability that the unemployed with search costs ω_i are registered (registration rate), $h_i \equiv \text{Prob}(s_i = 1)$, and following the recursive equation

$$h_i' = \max\Big\{(1 - e_i(p,1)f(\theta(p)))h_i, k_i(p')\Big\}. \tag{2.8}$$

Given a realization $p' \leq \bar{p}_i$, we have $k_i(p') = 1$, in which case every not yet registered unemployed with ω_i wants to register, irrespective of how long they have been unemployed, implying $h_i' = 1$. On the other hand, if $p' > \bar{p}_i$, nobody files for UI and only those who were registered previously and have not found a job remain registered, yielding $h_i' = (1 - e_i(p,1)f(\theta(p)))h_i$.

Average search effort given search cost ω_i is then given by

$$e_i = h_i e_i(p,1) + (1 - h_i)e_i(p,0),$$

while the unemployment rate among those with search cost ω_i follows recursively from

$$u_i' = (1 - e_i f(\theta(p)))u_i + \lambda(1 - u_i), \tag{2.9}$$

and aggregate unemployment can be found by averaging over all types

$$u = \int_0^\infty u_i \, dF(\omega_i). \tag{2.10}$$

Aggregate search effort is average search effort conditional on being unemployed

$$e = \frac{\int_0^\infty e_i u_i \, dF(\omega_i)}{\int_0^\infty u_i \, dF(\omega_i)}. \tag{2.11}$$

2.4.5 How Do Optimal Search Effort and Take-up Interact?

To characterize optimal search effort, denote by $s_i \in \{0,1\}$ whether i is registered. The first-order conditions for search effort $e_i(p, s_i)$ given productivity and registration status are then given by

$$\begin{aligned}
\omega_i e_i(p,0)^\kappa &= \delta f(\theta(p)) \left[\mathbb{E}_p W_i(p') - \mathbb{E}_p U_i(p')\right] \\
\omega_i e_i(p,1)^\kappa &= \delta f(\theta(p)) \left[\mathbb{E}_p W_i(p') - \mathbb{E}_p T_i(p')\right],
\end{aligned}$$

setting marginal search costs equal to marginal search return. These conditions pin down two potential search efforts, while in reality we only observe one of the two levels depending on whether i is registered. It can easily be shown that search effort is higher if not registered and that higher search costs imply lower search, as summarized in the following lemma:

Lemma 2. *Optimal search effort $e_i(p, s_i)$ satisfies the following:*

i Search effort is always higher if not registered: $e_i(p, 0) \geq e_i(p, 1)\ \forall\, i, p$

ii Higher search costs imply lower search: $\partial e_i(p, s_i)/\partial \omega_i < 0\ \forall\, i, p$

Proof. See appendix. □

Intuitively, while the already registered know that they will get a payment z if no job is found, the non-registered either will get no payment or will have to bear the claiming cost ψ if they file for UI in the subsequent period. Thus, the increase in value if a job is found is always higher for the non-registered unemployed, leading to higher search effort due to increasing marginal search costs. In addition, those with lower search costs will always exert higher search effort in equilibrium.

Moreover, under not very restrictive assumptions, individual search effort given registration status will turn out to be procyclical, as shown in the following proposition:

Proposition 2.3. *Denote by $g(p'|p)$ the conditional density of p' given p. Individual search effort conditional on registration status is procyclical, i.e. $\partial e_i(p, s_i)/\partial p > 0\ \forall\, i$, if $(1-\alpha)\varepsilon_{\theta,p} + \varepsilon_{g,p} > 0$, where $\varepsilon_{\theta,p} \equiv (\partial\theta(p)/\partial p)(1/\theta(p))$ denotes the elasticity of labor market tightness with respect to productivity and $\varepsilon_{g,p} \equiv (\partial g(p'|p)/\partial p)(1/g(p'|p))$ the elasticity of the conditional density of next period's productivity with respect to current productivity*[5].

Proof. See appendix. □

The procyclicality of individual search effort will not be crucial for the qualitative impact of the take-up channel in equilibrium. Nevertheless, it has to be pointed out that the condition for procyclicality does not turn out to be restrictive in practice. While plausible values for $\varepsilon_{\theta,p}$ range between 1 and 20 (see D. Mortensen and Nagypál (2007)), $\varepsilon_{g,p}$, assuming that innovations in the log-productivity process follow a normal distribution with variance σ^2, can be shown to equal $(\rho/\sigma^2)(p' - \rho p)$, which varies between -0.001 and 0.001 for the state-space and calibration used in the simulations.

Intuitively, why is this condition needed to ensure procyclicality? Strict convexity of search costs implies that search effort varies procyclically if the marginal search return does. The latter varies along two dimensions. On the one hand, as p increases, the job-finding rate increases, making the gain in value when finding a job more likely, implying a procyclical movement. On the other hand, for a given job-finding rate, the relative

[5] In the definition of the elasticities, note that p denotes *log* productivity.

expected values of working and staying unemployed change. The value of working increases because wages and the continuation value increase. However, the value of being unemployed also increases and might do so more strongly if the option value of being unemployed increases strongly. Hence, we can have a pro- and countercyclical movement in this second dimension. The condition in Proposition 2 is sufficient such that the second dimension does not outweigh the first.

Given optimal search effort, the non-registered unemployed decide every period whether to register. In this decision, they have to trade off a fixed take-up cost against expected future payments, discounted at the discount rate and the expected future job finding rates. On the other hand, the non-registered have higher job finding rates and their utility gain is higher if they find a job. Moreover, they still have the option of claiming in the future if conditions change. This gives the non-registered a higher option value. The unemployed will only be willing to claim UI if their probability of staying unemployed is sufficiently high, that is, if their job-finding rate is sufficiently low either due to a low tightness or a low search effort. Hence, the unemployed are more likely to claim if the tightness is low and their search costs are high, leading to a low search effort.

In Proposition 2.4, I show that if search effort is procyclical, the unemployed follow a cutoff rule, namely that for a given ω_i, there is some $\bar{p}_i$ so that i registers if $p \leq \bar{p}_i$. Moreover, while I have not been able to show this formally, I conjecture that $\bar{p}_i$ is increasing in ω_i, meaning that those with higher search costs are more likely to register. This conjecture has been confirmed in all numerical exercises.

Proposition 2.4. *Assume that $p \in [\underline{p}, \overline{p}]$, as well as $\partial e_i(p,1)/\partial p > 0$ and $\partial e_i(p,0)/\partial p > 0$ for all p and i. Then, the unemployed follow a cutoff rule. That is, there is a productivity level $\bar{p}_i$, so that $k_i(p) = \mathbf{1}[p \leq \bar{p}_i]$.*

Proof. See appendix. □

2.5 How does the Take-up Channel Affect the Cyclicality of Unemployment and Vacancies?

The aforementioned predictions on the interaction of take-up and search effort possibly have important implications for the cyclicality of the labor market aggregates. To intuitively see how, consider Figure 2.5. For simplicity, assume that all i are equally likely to be unemployed. The two solid lines correspond to $\int_0^\infty e_i(p,0)\,dF(\omega_i)$ and $\int_0^\infty e_i(p,1)\,dF(\omega_i)$, i.e. aggregate search effort if all i are not registered or registered, respectively. As argued before, search effort is always lower if registered. If we have $h_i \in (0,1)$, by contrast, but h_i does not depend on p, aggregate search effort $\int_0^\infty h_i e_i(p,1) + (1-h_i)e_i(p,0)\,dF(\omega_i)$ looks

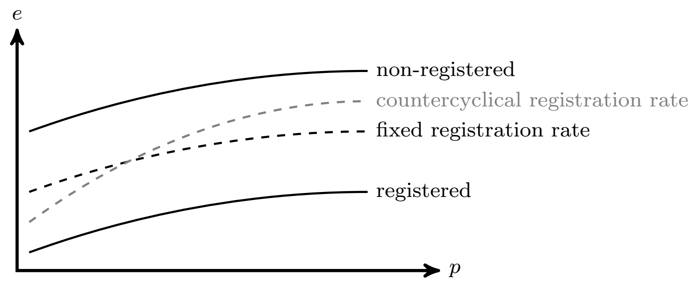


Figure 2.5: Search effort over the business cycle

similar to the dashed black line. On the other hand, if the unemployed are less likely to be registered for higher p, aggregate search effort turns out to be steeper, as exemplified by the gray dashed line. In a stochastic setting, this implies more volatility in search effort if its interaction with take-up is taken into account.

The rest of the present section will be devoted to getting a quantitative sense of the notion that the take-up channel amplifies fluctuations. To this end, I will simulate a calibrated version of the model, as explained in detail in the following.

2.5.1 Computation and Calibration

I assume that productivity innovations are normal with variance σ_ε^2 and approximate the stochastic process of p by a 51-state Markov chain using the algorithm due to Tauchen (1986). Steady-state productivity is standardized to 1. As was shown in the proof of Proposition 2.1, (2.4) defines a uniform contraction. Hence, I can iterate until convergence on (2.4) to find a policy function $\theta(p)$, which is independent of search effort over the business cycle. Given the block-recursive nature of the model, I can take $\theta(p)$ as given and turn to the worker-side of the economy.

A convenient consequence of the fact that $\theta(p)$ is invariant to search effort is that different workers do not interact, meaning that individual behavior is not affected by the distribution of ω. As a consequence, I can solve the model separately for different values of ω and aggregate afterwards to characterize the aggregate economy. Specifically, I use a grid of 100 values for ω_i and iterate on equations (2.5) - (2.7) to obtain policy functions $(e_i(p,0), e_i(p,1), k_i(p))$. Given initial conditions and a realization of the productivity process $\{p_t\}$, realizations of the registration rate h_{it} and unemployment rate u_{it} can be deduced using recursive equations (2.8) and (2.9).

Aggregate values are obtained by integrating over all i using the appropriate conditional distribution of ω_i, as in equations (2.10) and (2.11). For the unconditional distribution, I assume that $\log \omega_i \sim \mathcal{N}(\mu, \sigma^2)$, truncated so that $\omega_i \geq \underline{\omega} > 0$ to ensure job-finding rates below 1.

The model's periodicity is chosen to be a month divided by 28, roughly corresponding to one day. To calibrate the model, parameters δ, α, λ, ρ, σ_ε^2, c, γ, z, and κ are chosen according to the literature, while the remaining parameters w_0, m_0, μ, σ^2, ℓ, and ψ are chosen by requiring the certainty-equivalent version of the model to match certain long-run outcomes. Specifically, Hagedorn and Manovskii (2008) calculate a steady-state labor market tightness θ^* of 0.634 for the US. Moreover, for the US between 1951 and 2003, Shimer (2005a) estimates a monthly job-finding and job-separation rate of 0.45 and 0.026, respectively, implying a steady-state unemployment rate of $u^* = .026/(.026{+}.45) \approx 0.055$. At daily frequency, this translates into a steady-state job finding rate of $f^* = 1-(1-0.45)^{1/28} \approx 0.022$ and a job-separation rate of $\lambda = \frac{u^*}{1-u^*} f^* \approx 0.0012$. I set the elasticity of the vacancy-filling rate with respect to the labor market tightness α to 0.5, which is at the lower end of the range of plausible values (0.5 to 0.7) according to the survey by Petrongolo and Pissarides (2000). I follow Hagedorn and Manovskii (2008) in setting $c = 0.584$ and $\delta = .99^{1/84}$, corresponding to an annual interest rate of around 4 %. Given these parameter choices, solving the steady-state version of (2.4), I find

$$(c/m_0)(\theta^*)^\alpha\,(1/\delta - 1 + \lambda) = 1 - w_0,$$

which pins down the (approximate) average wage w_0. The matching parameter m_0, on the other hand, is chosen by requiring that

$$f^* = f(\theta^*) = m_0(\theta^*)^{1-\alpha}.$$

Haefke, Sonntag, and van Rens (2013) estimate the elasticity with respect to wages ($= 1-\gamma$) to be 0.3 for job-stayers and 0.8 for job-movers using CPS data. Given this background, I choose a cautious value of $\gamma = 0.25$, limiting the extent of fluctuations due to wage rigidity. Hagedorn and Manovskii (2008) measure productivity as seasonally adjusted quarterly real average output per person in the non-farm business sector constructed by the BLS and find the quarterly autocorrelation and unconditional standard deviation on the HP-filtered process (smoothing parameter 1600) (Prescott (1986)) to be 0.765 and 0.013, respectively. At daily frequency, this translates into $\rho = 0.9989$ and $\sigma_\varepsilon = 0.0011$. This completes the calibration of the labor demand side of the economy and determines the cyclical properties of the labor market tightness.

In structurally estimated equilibrium search models, Yashiv (2000) (Israeli data) and Christensen, Lentz, Mortensen, Neumann, and Werwatz (2005) (Danish data) each find search cost functions that are roughly quadratic. I hence set $\kappa = 1$. I fix the replacement rate z at a very cautious value of 0.2. Thus, as explained below, I will obtain a lower bound on the influence of the take-up channel. The remaining parameters μ, σ^2, ℓ, and ψ are chosen by numerically solving the certainty equivalent version of the worker problem and targeting the following quantities:

1. Using Austrian Social Security Data (ASSD)[6] and a sample of unemployed between 25 and 50 in the years 1984 until 2008, I find an average take-up rate of $\bar{s} = 0.5063$.

2. As shown in Figure 2.3 which is constructed from ASSD, the job-finding rate of the non-registered unemployed is about four times as large as of the registered. I target this ratio, taking into account that different ω_i's will sort into the two subgroups.

3. Average search effort among the unemployed is standardized to 1.

4. I choose ℓ so that the average steady-state flow utility while unemployed, i.e. the average of $\ell + s_i^* z - \omega_i/(1+\kappa)(e_i^*)^{1+\kappa}$, where e_i^* denotes the steady-state search effort of a worker with search costs ω_i taking into account i's steady-state registration status s_i^*, equals 0.7, following Hall and Milgrom (2008).

Table 2.3 summarizes the resulting calibration.

Parameter	Definition	Value
$\exp(\mu)$	Median of ω_i	0.171
σ^2	Dispersion of search costs	2.521
γ	Wage rigidity	0.200
w_0	Average wage	0.977
ℓ	Value of leisure	0.667
z	Replacement rate	0.200
ψ	Take-up cost	5.563
κ	Elasticity of marg. search cost	1.000
α	Elasticity of q w.r.t. θ	0.500
m_0	Matching parameter	0.027
c	Vacancy cost	0.584
δ	Discount rate	1.000
λ	Separation rate	0.001
ρ	Persistence of the productivity process	0.999
σ_ε^2	Variance of innovations in productivity process	0.001

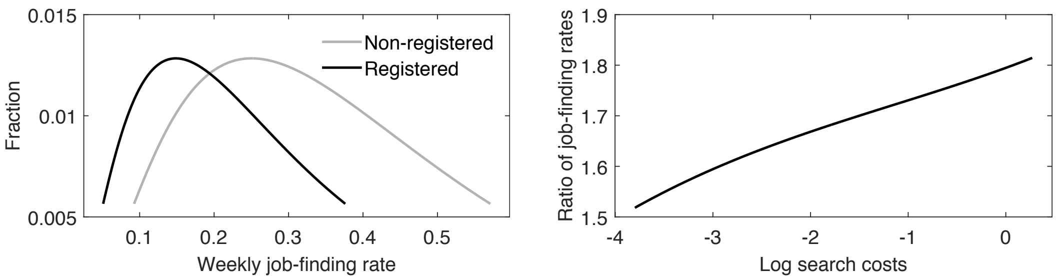
Table 2.3: Baseline calibration

Estimated take-up costs ψ are substantial – around 5.6 times the average daily wage. Accumulated UI benefits outweigh upfront take-up costs after around one month. However, this calculation does not take into account that registered unemployed have lower search costs than the non-registered.

[6]ASSD covers the universe of Austrian private sector workers, providing longitudinal information from 1972 onwards. The data has been collected in order to verify old-age pension claims and hence covers all information relevant for this aim. The dataset is useful here because we can observe UI take-up as well as individual search outcomes. ASSD has been used in a number of studies (e.g., Lalive, Van Ours, and Zweimüller (2006), Card, Chetty, and Weber (2007), Lalive, Schlosser, Steinhauer, and Zweimüller (2014)). For more information about the ASSD, see Zweimüller et al. (2009).

In order to understand the parameterization of the model, it is important to mention that the differences in observed search efforts between registered and non-registered unemployed can be generated by a continuum of possible values of z and σ^2. On the one hand, differences in search effort could largely be due to differences in expected monetary payments, while registered and non-registered unemployed do not differ much in their search costs. On the other hand, it could be that differences in payoffs do not play a big role, while the two groups differ a lot in their search effort because effort costs are very disperse and different people have sorted into the two groups. The first situation corresponds to a large value of z and a low value of σ^2, and vice versa for the second situation.

The take-up channel is the stronger, the closer we are to the former situation. If all differences between the two groups are due to differences in search costs, a change in the registration rate will only lead to a reshuffling of types between the two groups, while search effort conditional on ω_i will not change much. By contrast, if differences in search effort are largely due to differences in monetary incentives, individuals change their search effort when changing the registration status. This will amplify fluctuations in the aggregate economy.



(a) Steady-state job-finding rates

(b) Ratio of job-finding rate while non-registered and registered

Figure 2.6: Job-finding rates in the certainty-equivalent version of the model

Notes: Figure 2.6a plots the job-finding rates observed in the certainty-equivalent version of the model if either all unemployed are registered or non-registered. Figure 2.6b plots the ratio of weekly job-finding rates while non-registered and registered conditional on search costs. Both figures are obtained using the calibration in Table 2.3.

Setting $z = 0.2$, corresponding to a replacement rate of a little more than 20%, I use an estimate that is already very cautious for the American unemployment insurance system, let alone the system of many European countries. In particular, Anderson and Meyer (1997) calculate an after-tax replacement rate of 36%. This number does not account, however, for additional costs due to administrative requirements connected to receiving benefits and finite benefit reception length. By using a cautious value for z, we can be assured that the influence of the take-up channel is not due to an unrealistic parameterization of the model.

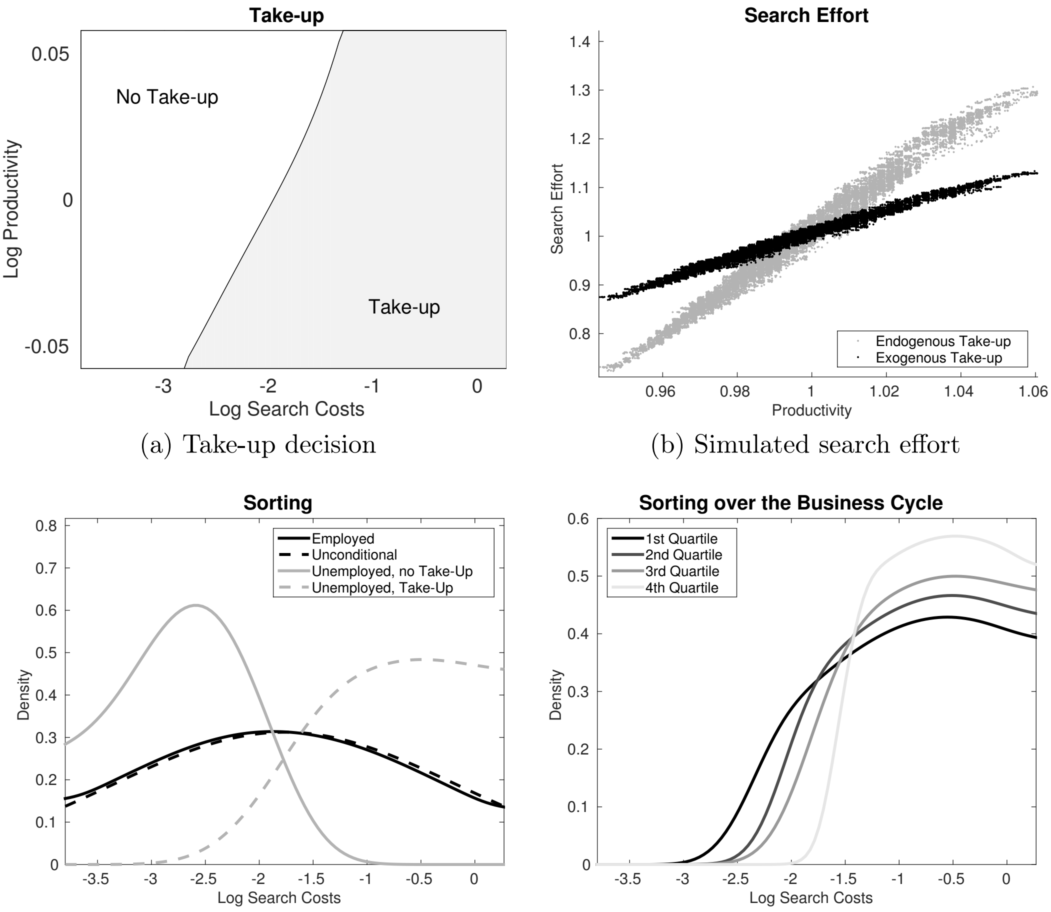
To translate the calibration of the search cost distribution into more easily interpretable terms, consider Figures 2.6a and 2.6b, summarizing properties of the certainty-equivalent version of the model. Figure 2.6a plots the observed weekly job-finding rates if either all unemployed are registered or non-registered. It can be seen that job-finding rates conditional on take-up status are quite disperse, while the shift in the job-finding rate following a change in take-up status is moderate in comparison. In Figure 2.6b, I plot the relative change in the job-finding rate if an unemployed switches from registered to non-registered – holding constant search costs and hence isolating the effect of the monetary incentive. This change is increasing in search costs, since differences in payoff are higher due to the longer expected length of unemployment in the case of high search costs. As can be seen, the ratio ranges between around 1.5 and 1.8 with an average of around 1.7, while the overall ratio, also accounting for the different distribution of search costs in both groups, was targeted to equal 4. Given the small value for z, only around $0.7/3 = 23.33\%$ of the observed differences in job-finding rates are attributed to monetary incentives, while the rest is due to selection.

2.5.2 Simulation Results

In the simulation exercise, I simulate two different economies: One with the baseline calibration (endogenous take-up) and one where take-up is fixed (exogenous take-up). That is, for all ω_i I fix k_i at its value obtained in the certainty-equivalent version of the model and do not allow it to vary over the business cycle. I generate 100 realizations[7] of $\{p_t\}$ of 3600×7 days length, eliminating the first 1200×7 days of every trajectory such that the results are not influenced by initial values, and aggregate to quarterly level. Every realization thus corresponds to 200 quarters, corresponding to 50 years of data. I then consider second-order moments of log-deviations from a HP trend with smoothing parameter 1600 (Prescott (1986)).

Before looking at the quantitative evaluation of the search effort channel, it is instructive to describe the qualitative features of the baseline model. In Figure 2.7a, I plot the take-up decision according to search costs and productivity. Combinations of search cost and productivity where UI is not claimed are shown in white, while those where it is claimed are shown in gray. On the one hand, as stated in Proposition 2.4, the unemployed – if they ever change their take-up status – follow a cutoff productivity rule. On the other hand, as was conjectured, the cutoff productivity is increasing in search costs such that

[7]For the time being, I have to make do with this low number of replications due to computational limits. Since the results hardly change when the exercise is repeated, the results seem to be robust, however.



(a) Take-up decision

(b) Simulated search effort

(c) Conditional search cost distributions according to labor market states

(d) Conditional search cost distributions in registered unemployment over the business cycle

Figure 2.7: Take-up and sorting in the simulated economy

Notes: Figure 2.7a summarizes equilibrium take-up function $k_i(p)$ generated by the model with the calibration in Table 2.3. The gray and white areas correspond to combinations of search costs and productivity where a take-up is made and not made, respectively. Figure 2.7b plots levels of search effort and productivity observed in the simulations of the model with parameters in Table 2.3. For the black dots, we additionally fix the take-up rate at its certainty-equivalent counterpart. Figure 2.7c plots kernel densities of the observed conditional distributions of search costs within different subgroups observed when simulating the model with the calibration in Table 2.3. Figure 2.7d plots kernel densities of the observed conditional distributions of search costs among the registered unemployed according to the quartile of current productivity when simulating the model with the calibration in Table 2.3.

unemployed with higher search costs are more likely to claim. In addition, there are also types that never change their decision within the considered state space.

With time-invariant heterogeneity in search costs, there is sorting of different types into different subgroups over time, as demonstrated in Figure 2.7c, plotting the search cost distribution among different groups if the model is simulated over time. Clearly, among the employed those with low search costs are overrepresented as they have higher job-finding rates. Among the unemployed, only those with low search costs sort into non-registered unemployment, while the registered unemployed are comprised of high search cost types. It is important to keep this in mind when interpreting the average job-finding rate shown in Figure 2.3. If we just regressed the job-finding rate on the amount of benefits received (effectively comparing groups with entirely different search cost distributions), we would confound this with the differences in search effort due to self-selection. The model, however, explicitly takes this into account.

Another important qualitative finding is that the composition of the registered unemployed changes considerably over the business cycle, as can be seen from Figure 2.7d. If conditions are favorable, only those with very high search costs sort into registered unemployment. This is different during downturns, when also those with low search costs sort into registered unemployment. This might lead to different reactions to changes in incentives depending on the business cycle.

In Figure 2.7b, I plot the simulated counterpart of the two dashed lines in Figure 2.5. In particular, I plot all combinations of productivity and aggregate search effort obtained in a simulation of the economy with endogenous and exogenous take-up. Clearly, the message of Figure 2.5 is corroborated in the sense that the volatility of search effort is amplified if we account for the take-up channel. What did not become clear in Figure 2.5 is that the dispersion of search effort levels for a given productivity level is also affected. There is no deterministic relationship between productivity and aggregate search effort since the latter depends on the composition of the unemployed which is determined by history. With the distinction between registered and non-registered unemployment there is another source of history determined heterogeneity. In particular, if there have been many adverse shocks in the past, many unemployed have sorted into registered unemployment and they will only leave it by finding a job, as argued before. The high number of registered unemployed will then cause aggregate search effort to be lower, even though current productivity is at the same level.

Finally turning to the quantitative results, I tabulate the second-order moments of the two simulated economies in Table 2.4. For reference, I also report summary statistics calculated from US data by Hagedorn and Manovskii (2008). Concentrating for a moment on the simulated correlations, we conclude that both models have qualitatively similar implications that are broadly in line with the previous literature and observed moments. All the signs are correct while the absolute magnitudes are generally too high, which is a common feature of these models. Turning now to the standard deviations, the two models differ more markedly. In particular, while θ does not differ in both models since the firm's decision is invariant to take-up behavior and search effort, all other volatilities turn out to be higher in the model with endogenous take-up. In particular, the volatility of search effort is almost threefold if we account for moves in and out of registered unemployment. This increased volatility of search effort also amplifies fluctuations of unemployment, vacancies, and the vacancy-unemployment ratio. Remarkably, the wage rigidity required to match a considerable share of the volatility of the vacancy-unemployment ratio is very low. The elasticity of wages with respect to productivity is as high as $1 - \gamma = 0.8$, while Hagedorn and Manovskii (2008) require a wage elasticity of 0.449.

	Standard deviation			Correlation with productivity		
Variable	Exogenous Take-up	Endogenous Take-up	Data	Exogenous Take-up	Endogenous Take-up	Data
u	0.085	0.117	0.125	-0.949	-0.921	-0.302
v	0.078	0.093	0.139	0.954	0.920	0.460
e	0.029	0.067	–	0.984	0.981	–
v/u	0.156	0.194	0.259	0.996	0.994	0.393
θ	0.127	0.127	–	0.996	0.996	–
p	0.013	0.013	0.013	1.000	1.000	1.000

Table 2.4: Results from the model with endogenous take-up, exogenous take-up and quarterly US data, 1951:I to 2004:IV

Notes: All variables are reported in logs as deviations from an HP trend with smoothing parameter 1.600. Calibrated parameter values are described in Table 2.3. In the model with exogenous take-up, the take-up probability is held fixed at its steady-state value. US data: Seasonally adjusted unemployment, u, is constructed by the BLS from the Current Population Survey (CPS). The seasonally adjusted help-wanted advertising index, v, is constructed by the Conference Board. Both u and v are quarterly averages of monthly series. Average labor productivity p is seasonally adjusted real average output per person in the nonfarm business sector, constructed by the BLS from the National Income and Product Accounts and the Current Employment Statistics.

The preceding exercise demonstrates that the model is generally consistent with reality in terms of generated volatilities and correlations. As a further check of the model's performance, I will feed actual instead of simulated productivity data into the model and check how the model-generated take-up rate compares to observed data.

Following Shimer (2005a), I use real real output per worker in the nonfarm business sector, which is in quarterly periodicity and reported by the BLS, as a proxy variable for productivity. This series is also the basis of Table 2.4. I interpolate this time series to obtain daily data. Proceeding as in the simulations I solve for all model-generated

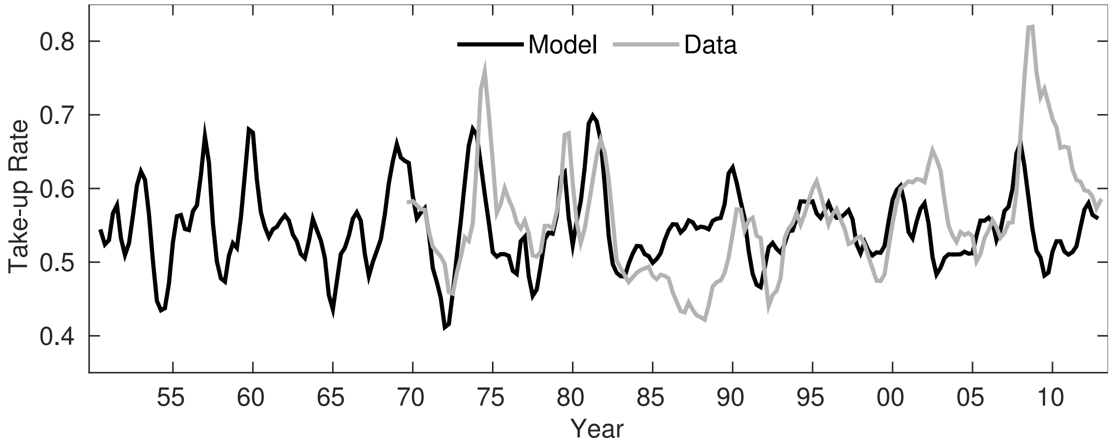


Figure 2.8: Simulation of historical data

Notes: The gray line corresponds to the ratio of Initial Jobless Claims, constructed by the U.S. Department of Labor, and separations, estimated from CPS data using the methodology detailled in Appendix A. The variable is a quarterly average of a monthly series. The black lines correspond to model-generated counterparts, using the calibration in Table 2.3 and taking actual productivity (seasonally adjusted real average output per person in the nonfarm business sector, constructed by the BLS from the National Income and Product Accounts and the Current Employment Statistics) as input.

variables using the same calibration. As start values for the recursive variables I use the steady-state counterparts instead of actual realizations, which only works against the model's ability to match the data. The data on unemployment and vacancies also coincide with those used in Table 2.4. As a measure of take-up, I use Initial Jobless Claims over separations as in Figure 2.1.

The results of this exercise are given in Figure 2.8. The model implied take-up rates are quite close to the data. There are only two exceptions: On the one hand, during the 80s, the model predicts considerably higher take-up rates. This gap can be explained by a tax reform in 1982 which significantly decreased the after-tax replacement rate and lead to a strong decline in UI take-up, as analyzed in detail by Anderson and Meyer (1997). On the other hand, the take-up rate was higher than predicted by the model during the Great Recession. During this time, maximum benefit durations were extended considerably (from the usual 26 weeks to up to 99 weeks) as part of the Extended Benefits program (EB) and Emergency Unemployment Compensation (EUC08), which effectively lead to a higher expected payoff of claiming UI.

It has to be pointed out that the calibration only targeted the average take-up rate and relative average job-finding rates when registered and non-registered. That the model is able to replicate the observed fluctuations in take-up while also matching the other variables is due to the structure of the model. This makes me confident that the mechanism proposed in this model is close to the trade-off that the unemployed face in reality.

2.5.3 Introducing Nash Bargaining

How are the model's cyclical predictions affected if we instead assume Nash bargaining, as is more common in the DMP model? I will explore this question in a slightly simplified version of the model. Following the strategy used by Pissarides (2009), I abstract from aggregate uncertainty (p is fixed over time) and compare different steady-states instead. This means that the take-up decision is fixed for every worker i and will not change during the spell.

Differing from the previous setting, firms and workers engage in Nash bargaining when matched to each other. Bargaining is assumed to occur only at the beginning of the spell, where take-up costs are sunk. This rules out the possibility that wages are re-bargained once take-up costs are not sunk anymore. While bargaining is pairwise and wages are allowed to depend on search costs ω_i and take-up status, I assume random search, meaning that vacant firms cannot direct their search toward specific workers. In Appendix B, I describe the full model.

A quantitative exercise will give us some intuition regarding the role of endogenous take-up in this model. I solve the model for different values of p and calculate the elasticities of all endogenous variables. In doing so, I use the calibration in Table 2.3. The condition due to Hosios (1990) provides a natural benchmark and I hence choose bargaining power β equal to the elasticity of $q(\theta)$ with respect to θ. Since before the wage parameter w_0 was pinned down by steady-state labor market tightness, I now adjust hiring cost c so that labor market tightness equals its steady-state value for $p = 0$. For comparison, I also calculate the implied elasticities in the steady-state version of the baseline model. Since it is a known shortcoming of the model with Nash bargaining that the wage is too elastic, I need to reduce wage rigidity γ to make the numbers comparable. I choose γ so that the elasticity of θ coincides for exogenous take-up, which again allows me to quantify the net effect due to the take-up channel.

The results are presented in Table 2.5. The exercise reveals that endogenous take-up still implies more amplification in the model with Nash bargaining. Moreover, amplification seems to increase compared to the baseline model. The observed patterns are instructive. Call $\varepsilon_{x,p}$ the elasticity of variable x with respect to productivity. The most important observation is that while $\varepsilon_{\theta,p}$ is invariant to take-up in the baseline model by construction, under Nash bargaining firms vary vacancies more strongly even conditional on search effort. As $\varepsilon_{e,p}$ is almost unaffected and $\varepsilon_{v/u,p} = \varepsilon_{e,p} + \varepsilon_{\theta,p}$, the effect on θ is also the reason for the increased amplification in the vacancy-unemployment ratio, while similar conclusions hold for unemployment and vacancies.

How does this effect come about? While the baseline model had a block-recursive structure in that worker behavior did not feed back into the firm's problem, firms now

	Elasticity w.r.t. productivity				
	Baseline		Nash Bargaining		
Variable	Exogenous Take-up	Endogenous Take-up	Exogenous Take-up	Endogenous Take-up	Data
u	4.430	6.712	4.337	7.791	9.615
v	1.754	1.927	1.748	3.134	10.692
e	3.090	5.544	2.991	5.506	–
v/u	6.185	8.639	6.085	10.925	19.923
θ	3.095	3.095	3.095	5.419	–

Table 2.5: Elasticities in the baseline and Nash bargaining model with endogenous take-up, exogenous take-up and empirical elasticities (quarterly US data, 1951:I to 2004:IV)

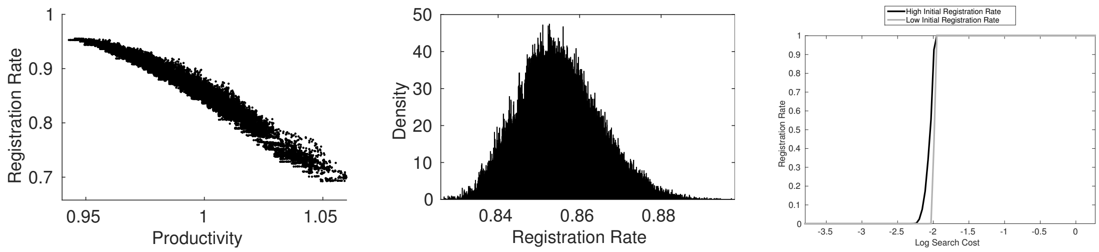
Notes: Calibrated parameter values are described in Table 2.3 and in the main text. The baseline model is a steady-state version of the model described in Section 2.4. The model with Nash bargaining is described in Appendix B. The model See the notes of Table 2.4 for details regarding the data.

react to worker behavior. In Appendix B, I show that the free-entry condition takes the form

$$\frac{c}{\delta q(\theta)} = (1-\beta)\frac{\int_0^\infty e_i u_i S_i(h_i)\, dF(\omega_i)}{\int_0^\infty e_i u_i\, dF(\omega_i)},$$

where β denotes workers' bargaining power, u_i, e_i, and h_i denote equilibrium unemployment, search effort, and take-up status of a worker with search costs ω_i, respectively, and $S_i(h)$ denotes the joint surplus when a firm is matched to a worker with search costs ω_i, who had take-up status h_i. The zero-profit condition equates the expected hiring cost to the expected profit, which is $(1-\beta)$ times the expected surplus, where the expectation is taken with respect to the probability of meeting a worker with ω_i among the unemployed. It turns out that shifts in the probability of meeting a worker have very little quantitative significance and hence the effect is driven by the surplus function $S_i(h_i)$.

Since workers' outside value increases when registered, we have $S_i(0) > S_i(1)\, \forall i$. If a firm meets a worker on benefits, bargained wages are driven up ceteris paribus and hence profits decrease. During upturns, fewer workers claim UI which drives up average surplus, increasing incentives for vacancy creation. Thus, in the model with Nash bargaining, take-up causes amplification in two distinct ways. On the one hand, as in the baseline model fluctuations in search effort increase as workers shift back and forth between the registered and non-registered state. On the other hand, under Nash bargaining take-up also affects wages, inducing an endogenous wage rigidity.



(a) Simulated registration rate (b) Simulated registration rate given $p = 0$ (c) Initial values for h_i

Figure 2.9: Registration rate over the business cycle and conditional on productivity; initial values chosen for the registration rate

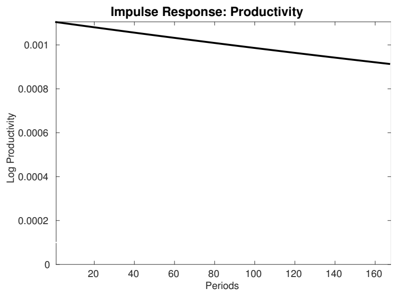
Notes: Figure 2.9a plots levels of the registration rate and productivity observed in the simulations of the model with parameters in Table 2.3. Figure 2.9b plots the empirical distribution of observed values of the registration rate given $p = 0$. Figure 2.9c plots the initial values for h_i chosen for the impulse response graphs.

2.5.4 Path Dependence

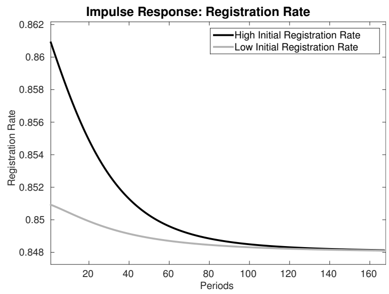
As is apparent from Figure 2.9a, the registration rate not only covaries systematically with productivity, but also displays considerable dispersion for given values of productivity. This becomes clearer from Figure 2.9b, where I plot the simulated distribution of registration rates conditional on log productivity being equal to its steady-state value. As already explained, this variation is due to path dependence: Past adverse shocks increased past claiming, which is why the registration rate is now higher even though current productivity is the same.

Since there is no one-to-one mapping between productivity and the registration rate, it makes sense to ask whether the current registration rate affects the way the economy reacts to shocks. To explore this question, I compare impulse response graphs for initially high and low registration rates. In Figure 2.10, I plot the impulse response graphs, depicting the dynamic reaction to a one-standard deviation shock to productivity. Of course, since we are talking about the daily standard deviation, the numbers are rather small, but the basic pattern would not change if we chose another periodicity. Initial values of all variables are chosen to be the steady-state values, except for the registration status given search cost, h_i, which we either fix at the 25th or 75th percentile of the observed distribution given $p = 0$ and ω_i. Figure 2.9c plots the values for h_i chosen for the two different scenarios.

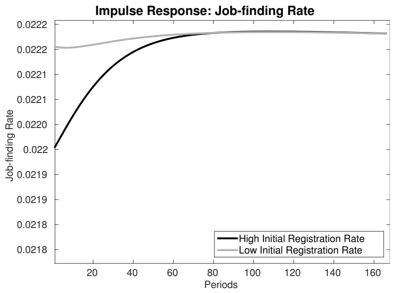
Figure 2.10 summarizes the time paths of productivity as well as for the registration rate, the aggregate job-finding rate and the unemployment rate for the two scenarios. In Figure 2.10b, we see that the gray line starts out at a lower level than the black line. Even though take-up behavior is completely identical in both scenarios (as k_i only depends on current productivity), it takes around three months until the influence of initial



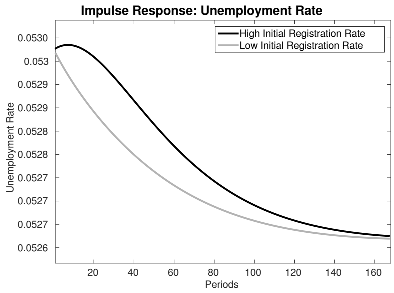
(a) Productivity



(b) Registration Rate



(c) Job-finding Rate



(d) Unemployment Rate

Figure 2.10: Impulse response graphs: Low vs. high initial registration rate

Notes: The figures plot the dynamic reaction to a one-standard deviation shock in productivity over the period of six months. Figures 2.10b, 2.10c, and 2.10d plot the model-generated values of the registration rate, the job-finding rate, and the unemployment rate. For the gray lines, I assume that h_i starts out at the 25th percentile of the observed distribution given $p = 0$ and ω_i, while for the black lines I start out at the 75th percentile.

conditions has disappeared. This difference in the registration rate directly affects job-finding rates, as is apparent in Figure 2.10c. If the economy starts out with an initially high registration rate, the job-finding rate remains visibly lower for at least two months. This difference leads to a much slower adjustment of the unemployment rate (Figure 2.10d). Since the initially low job-finding rate implies a higher steady-state unemployment rate than the start value, the unemployment rate even increases initially. In total, it takes around six months until the unemployment rate has caught up with the scenario where the registration rate was initially low.

The economy's reaction to a positive productivity shock is hence very different depending on the situation we inherited from past shocks. In one case, past adverse shocks have led to an accumulation of UI recipients. These individuals display lower search effort even though current conditions are the same. In the other case, higher productivity is quickly transmitted to lower unemployment as the aggregate job-finding rate increases much more quickly. This observation suggests take-up as a cause of hysteresis in the short run. Short-lived and shallow downturns are likely to lead to less persistent periods of high unemployment. Note that the persistence is higher if the exit rate from unemployment is lower since the registration rate dies down less quickly. Since the model is calibrated to the US economy featuring relatively high degrees of reallocation, this effect should be much stronger for European economies.

2.5.5 Optimal Unemployment Insurance along the Business Cycle

The model makes rich predictions on the variation of take-up and search effort as well as the composition of registered unemployed over the business cycle. Since all of the former affect the optimal design of unemployment insurance, it makes sense to explore the model's implications regarding the question how benefits should vary over the business cycle. Since a full characterization of optimal unemployment insurance in the present model is very complicated and clearly goes beyond the scope of the paper, a back-of-the-envelope calculation can give us an idea of the qualitative effect. In particular, I will simplify the analysis by only considering permanent and unanticipated changes in unemployment insurance. This allows me to maintain the structure of the model, as individuals' expectations are unaffected. Since the optimal permanent level of UI will be different depending on the current state of the economy, this still allows us to draw qualitative conclusions about optimal UI along the business cycle.

Specifically, assume that the government has to decide on the optimal level of z, which is financed by a lump-sum tax τ on workers. Moreover, assume that individuals' utility from consumption is described by a function $v(c)$, which is strictly increasing and strictly concave. The following proposition gives an implicit condition for the optimal permanent level of unemployment insurance in this setting:

Proposition 2.5. *The optimal permanent level of unemployment insurance in period t_0 is implicitly defined by*

$$\frac{v'(c_u) - v'(c_e)}{v'(c_e)} = \frac{\sum_{t=t_0}^{\infty} \delta^{t-t_0} u_{1t} \left(\frac{\partial u_{1t}}{\partial z} \frac{z}{u_{1t}} + \frac{\partial u_t}{\partial z} \frac{z}{u_t} \frac{u_t}{1-u_t} \right)}{\sum_{t=t_0}^{\infty} \delta^{t-t_0} u_{1t}},$$

where c_e denotes consumption of workers, c_u denotes consumption of registered unemployed, u_{1t} denotes the number of registered unemployed in period t and u_t denotes the number of unemployed in period t.

If third-order terms of $v(c)$ are small ($v'''(c) \approx 0$),

$$\frac{v'(c_u) - v'(c_e)}{v'(c_e)} \approx \gamma \frac{c_e - c_u}{c_e},$$

where γ is the coefficient of relative risk aversion.

Proof. See appendix. □

To make sense of this condition, I rewrite it in the following way:

$$\sum_{t=t_0}^{\infty} u_{1t}\delta^{t-t_0}v'(c_u) = \underbrace{\sum_{t=t_0}^{\infty} u_{1t}\delta^{t-t_0}v'(c_e)}_{\equiv M} + \underbrace{\sum_{t=t_0}^{\infty} u_{1t}\left(\frac{\partial u_{1t}}{\partial z}\frac{z}{u_{1t}} + \frac{\partial u_t}{\partial z}\frac{z}{u_t}\frac{u_t}{1-u_t}\right)\delta^{t-t_0}v'(c_e)}_{\equiv B}$$

Increasing UI by one unit for all subsequent periods increases aggregate utility by increasing consumption of the unemployed by approximately $\sum_{t=t_0}^{\infty} u_{1t}\delta^{t-t_0}v'(c_u)$. In the optimum, this has to be equal to the decrease in aggregate utility due to higher taxes and hence lower consumption of the employed. If behavior did not respond to z, this would be given by M, which is the mechanical effect. In this case, optimal UI would imply $c_e = c_u$, i.e. full insurance. However, there is also a behavioral effect, given by B: Higher z increases unemployment and lowers the number of tax payers, which leads to a further reduction in consumption of the employed. Expressed in per-period terms, we have

$$v'(c_u) = \left(1 + \underbrace{\frac{\sum_{t=t_0}^{\infty} \delta^{t-t_0}u_{1t}\left(\frac{\partial u_{1t}}{\partial z}\frac{z}{u_{1t}} + \frac{\partial u_t}{\partial z}\frac{z}{u_t}\frac{u_t}{1-u_t}\right)}{\sum_{t=t_0}^{\infty} \delta^{t-t_0}u_{1t}}}_{\equiv \mathcal{C}}\right) v'(c_e)$$

For every additional dollar the unemployed receive, consumption of the employed has to be decreased by $1+\mathcal{C}$ dollars, where $\mathcal{C}$ summarizes the average behavioral response and will henceforth loosely be called the welfare cost of increasing unemployment insurance[8]. $\mathcal{C}$ drives a wedge between marginal utilities. Loosely speaking, the first-order condition equates the consumption smoothing benefits of increasing UI on the left-hand side to the welfare costs on the right-hand side. It is important to bear in mind that the condition does not allow to calculate optimal unemployment insurance directly, since the right-hand side of the equation is endogenous to unemployment insurance. Hence, we would have to deduce how the right-hand side changes with z from the model. In any case, however, we can assess the impact of a small reform around the current state: If the right-hand side is larger, then an increase in unemployment insurance will have a negative impact on aggregate welfare.

$\mathcal{C}$ can easily be simulated by solving for the policy functions given a small change in z. I then generate 300 realizations of the productivity process using the same procedure as in Section 2.5.2. By comparing the baseline realizations and the realizations in an economy where z is changed after period t_0, we are able to approximate the elasticities of u_{1t} and u_t with respect to z.

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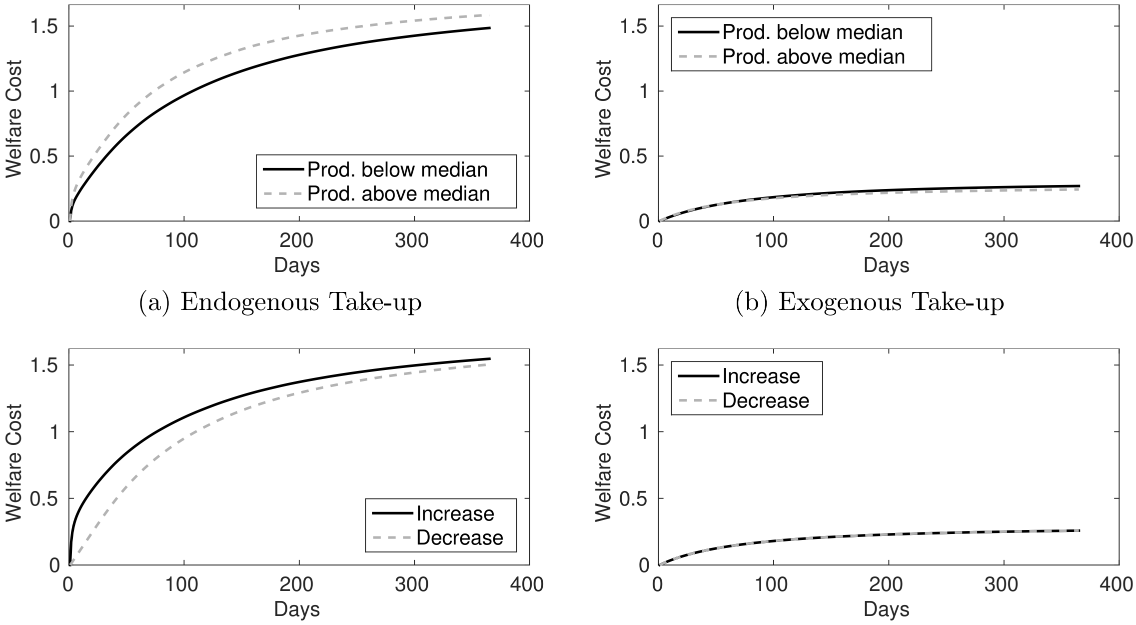
[8] Of course, if we are considering a decrease in unemployment insurance, the cost becomes a gain, as workers' consumption increases by more than one-to-one due to lower unemployment.



(a) Endogenous Take-up

(b) Exogenous Take-up

(c) Endogenous Take-up

(d) Exogenous Take-up

Figure 2.11: Simulated welfare cost of increasing z

Notes: The figures plot the welfare cost $\mathcal{C}(t_0, t)$ for various constellations. In Figure 2.11a, we compare economies with initial productivity below or above median for endogenous take-up, while Figure 2.11b repeats the exercise for exogenous take-up. In Figure 2.11c, we compare the cost of an increase in z to a decrease for endogenous take-up, while Figure 2.11d repeats the exercise for exogenous take-up.

In Figure 2.11, I plot simulated values of the welfare cost of changing z in truncated at t,

$$\mathcal{C}(t_0, t) \equiv \frac{\sum_{t=t_0}^{t} \delta^{s-t_0} u_{1s} \left(\frac{\partial u_{1s}}{\partial z} \frac{z}{u_{1s}} + \frac{\partial u_s}{\partial z} \frac{z}{u_s} \frac{u_s}{1-u_s} \right)}{\sum_{t=t_0}^{t} \delta^{s-t_0} u_{1s}},$$

which corresponds to the welfare cost if the change in z were abandoned after period t and the economy would jump to its baseline path afterwards. While this measure converges to the true welfare cost of a permanent increase in z for t going to infinity, it should give an idea about the short term effects for lower t.

In Figure 2.11a, I consider the welfare cost for the baseline economy depending on whether productivity was initially below or above median. Figure 2.11b repeats the exercise assuming exogenous take-up. A first thing to notice is that the welfare cost is markedly higher if take-up is endogenous. If take-up increases as z is increased, the behavioral effect is higher, a fact first noted by Kroft (2008). Moreover, the welfare cost converges to around 3 for the baseline economy, which would require a consumption drop $(c_e - c_u)/c_e$ of 100% even with a coefficient of relative risk aversion as high as 3. This is a sign that the level of consumption of the unemployed is too high. This is not a surprising finding, as the literature usually finds optimal replacement rates of around 50% (e.g., Chetty (2006), Gruber (1997)), while the given calibration sets average flow utility at around 60%.

More importantly, however, endogenous take-up appears to have sizeable consequences for welfare costs along the business cycle. While initial productivity does not seem to matter much if take-up is exogenous, welfare costs are much higher if initial conditions are good in the case of endogenous take-up. The behavioral effect of increasing unemployment insurance is higher if the economy is in a boom. The reasons are twofold: On the one hand, during downturns, take-up does not increase strongly if z is increased, as most unemployed have already claimed in the past. On the other hand, if conditions are good, the pool of the registered unemployed tilts toward those with very high search cost, whose search effort is more elastic to UI as their expected duration of unemployment is longer as could be seen from Figure 2.7d. This finding suggests that a countercyclical unemployment insurance would be welfare improving. This corresponds to the result by Landais et al. (2014), while the mechanism is different: While they emphasize externalities of search effort going through firms' reaction, i.e. through reactions of θ, this mechanism is absent by assumption in the baseline model. Here, the macro elasticity of unemployment is equal to the micro elasticity of unemployment and take-up affects both.

The model also implies an asymmetric response to increases and decreases of unemployment insurance. This is because an increase in UI leads to an immediate inflow into registered unemployment, while after a decrease the unemployed stay registered until they find a job. While for Figures 2.11a and 2.11b, the average behavioral response was calculated by averaging over the effects of a decrease and increase in z, in Figures 2.11c and 2.11d I now calculate the welfare costs separately. As expected, while this dimension is virtually irrelevant for exogenous take-up, asymmetry is apparent in the case of endogenous take-up. This asymmetry disappears in the long run, as in the case of a decrease in z workers who would not claim anymore eventually attrition out of registered unemployment. While the present qualitative analysis does not allow to quantify the effect entirely, this should serve as a caveat against varying UI over time. Given the model's predictions, increasing the replacement rate has a stronger short-term effect on the unemployment rate than a decrease later on. This may cause the unemployment rate to ratchet up over time in the presence of a variable replacement rate.

Clearly, the present analysis only gives a rough sense of how take-up might affect our conclusions regarding optimal UI along the business cycle. Even so, we get the impression that the implications are qualitatively and quantitatively relevant and that a more thorough analysis might be worthwhile.

2.6 How does the Take-up Channel Affect the Optimal Timing of Unemployment Insurance?

In the present framework, heterogeneity in search costs accounts for differences in job-finding prospects that are present even conditional on monetary incentives. In reality, these differences could be due to differences in search ability but also due to various forms of skill mismatch. This implies that among the pool of the unemployed, the plight of unemployment in absence of unemployment insurance, here measured by the discounted utility if not registered, $N_i(p)$, might display large variation. While some people manage to find a job rather quickly and hence do not suffer larges losses in their utility, others face extended spells of unemployment.

Assume the government, or henceforth the principal, offers an unemployment insurance contract with the aim of buffering large losses in utility by guaranteeing a minimum promised utility level, $\bar{V}$, to every unemployed upon entry in unemployment. Among all contracts that achieve this goal, the principal wants to find the one that minimizes the cost of providing it. Also, assume that there are some workers who already achieve $\bar{V}$ if not registered (henceforth referred to as high types), while there are other workers who need to be insured (henceforth low types). If search costs are observable, the principal will not offer an unemployment insurance contract to high types and offer the cost-minimizing contract only considering low types. In practice, however, search costs are unobservable to the principal. This implies that, assuming that pooling is not optimal, the contract has to be designed in a way that has high types self-select into non-registered unemployment.

Intuition suggests that this additional incentive constraint implies backloading of the scheme: If the principal wants to grant a minimum utility level to low types, while not exceeding a certain utility for high types, this is achieved by paying more transfers in the future, as low types face a higher probability of still being unemployed. This enables the principal to screen the unemployed, as only low types sort into registered unemployment. Backloading comes at a gain, since high types are excluded which lowers the cost of providing the contract. However, it also comes at a cost, since we have to deviate from the cost-minimizing contract for the low types in order to exclude the high types. Hence, pooling, where the principal also provides insurance to those who don't need it, might also be optimal.

This conclusion hence contrasts with the early finding due to Shavell and Weiss (1979) and followed up upon by H. A. Hopenhayn and Nicolini (1997), that benefits should be decreasing throughout the spell to provide incentives to search (henceforth referred to as the Shavell-Weiss contract). While this result is also sensitive to other adaptions of the basic model – e.g. Shimer and Werning (2008) show that optimal benefits are nearly constant once we allow for savings – the effect of endogenous take-up decisions is a mechanism that has not been considered so far.

2.6.1 Environment

To explore what the take-up channel implies for the optimal time-structure of unemployment benefits, I focus on the steady-state version of the model laid out in section 2.4, setting $p = 0$ in every period. In order to introduce a consumption-smoothing objective, I add curvature to the model by assuming that individuals derive flow utility $u(c)$ from consumption c, where $u''(c) < 0 < u'(c)$. I assume that workers cannot save. On the one hand, this simplifies the analysis and will yield the result due to Shavell and Weiss (1979) as a natural benchmark. On the other hand, this will make it more difficult to generate backloading in the benefit schedule, since, as mentioned above, allowing for savings works against a downward sloping benefit schedule.

To simplify notation, I fix $f(\theta) = 1$ and rescale search effort accordingly. In $t = 0$, all workers start out as unemployed. The stationary setting implies that workers either claim in $t = 0$ or never. If they find a job, they stay employed forever (I set $\lambda = 0$), earning value

$$W = \frac{u(w(0))}{1-\delta}.$$

Denote by $N(\omega)$ the value if not registered of type ω, while $T(t;\omega)$ denotes the value of type ω if unemployed and having been in insured unemployment for t periods. In order to simplify the analysis, I assume that there are only two types, a low type and a high type with search cost parameters ω_l and ω_h, where $\omega_l > \omega_h$, respectively. The respective population shares are given by $q(\omega_l)$ and $q(\omega_h)$. The remainder of the model stays unchanged.

At $t = 0$ a risk-neutral principal offers unemployment insurance as a take-it-or-leave-it contract to each unemployed individual. The contract specifies net transfers as a function of unemployment duration, $z(t)$, and a recommended action (search effort if registered) $e(\omega, t)$ as a function of realized history. The principal neither observes the search cost ω nor $e(\omega)$. For technical reasons, I need to assume that benefits are paid up to period T, which is without loss of generality as T can be chosen to be arbitrarily large. The principal chooses the optimal contract so as to minimize the cost of providing the contract,

$$C = \sum_{\omega\in\{\omega_l,\omega_h\}} s(\omega)q(\omega)\left[z(0) + \sum_{t=1}^{T}\delta^t\prod_{\tau=0}^{t-1}(1-e(\omega,\tau))z(t)\right],$$

subject to

$$s(\omega)(T(0;\omega)-\psi) + (1-s(\omega))N(\omega) \geq \bar{V} \;\; \forall\omega,$$

where $s(\omega) \in \{0, 1\}$ denotes the take-up status of type ω and $\bar{V}$ denotes minimum promised utility. That is, the principal wants every unemployed to attain a utility level of at least $\bar{V}$, either if insured or not. To rule out the trivial solution where UI is either offered to nobody or both types, we assume $N(\omega_l) < \bar{V} \leq N(\omega_h)$, i.e. the low type needs a transfer in order to achieve the required level of utility, while the high type already enjoys sufficient utility in autarky.

The setting is similar to Hagedorn, Kaul, and Mennel (2010), who characterize the optimal time structure of benefits if the principal can condition the time structure of benefits on unobserved heterogeneity. The difference in the setting adopted here is that the principal only offers one time structure to every type and agents can opt out by not claiming benefits. In particular, their setting implies that the highest types are offered the first-best contract (no distortion at the top), while here the contract is only offered to the low types (or everyone). More importantly, however, the present setting is a natural extension of the realistic take-up setting analyzed in this paper.

2.6.2 Benchmark Cases

In the case of full information, where the principal observes workers' types as well as their search effort decisions, it is straightforward to verify that the principal will offer a constant benefit schedule to low types while excluding the high types. The risk neutral principal insures the risk averse agent fully against income fluctuations, while prescribing a constant effort level.

If the principal observes types, but not search effort, he will still exclude high types from the contract. The problem then reduces to the classic setting with moral hazard and the principal will offer the Shavell-Weiss contract to the low types.

This is not generally possible, however, if types are not observed. Unless ω_h is very low compared to ω_l, the high types will always have an incentive to sort into the Shavell-Weiss contract offered to the low types. But the Shavell-Weiss contract is only the cost minimizing contract if high types can be excluded. This means that the cost minimizing contract will look different, either because both types are offered a contract (pooling) or because types have to be separated.

2.6.3 Simplified Model

The basic mechanism is best demonstrated in a stylized version of the model: Assume we only have two periods. In the first period, workers start out as unemployed, choose whether to claim UI and search optimally for a job. If a job is found, they are employed in the second period, while in the opposite case they stay unemployed. In order to simplify the exposition, I assume $u(c) = \log(c)$ and standardize $w(0) = 1$, so that $u(w(0)) = 0$. I also set $\kappa = 1$ and $\delta = 1$.

If not registered, the unemployed earn value

$$N(\omega) = \max_e \left\{ \log \ell + e \cdot 0 + (1 - e) \log \ell - \frac{\omega}{2} e^2 \right\} = 2 \log \ell + \frac{1}{2\omega} (\log \ell)^2,$$

where the second equality follows by substituting the first-order condition for optimal search effort into the value function.

If registered, a worker's value in period 0 with benefit schedule $(z(0), z(1))$ is given by

$$\begin{aligned} T(z(0), z(1), \omega) &= \max_e \left\{ \log(\ell + z(0)) + e \cdot 0 + (1 - e) \log(\ell + z(1)) - \frac{\omega}{2} e^2 \right\} \\ &= \log(\ell + z(0)) + \log(\ell + z(1)) + \frac{1}{2\omega} (\log(\ell + z(1)))^2, \end{aligned}$$

where the second equality again follows using the first-order condition for optimal search effort. As before, a worker claims UI if $T(z(0), z(1), \omega) - \psi \geq N(\omega)$. Note that $\partial(T(z(0), z(1), \omega) - N(\omega))/\partial\omega > 0$, i.e. workers with higher search costs are more likely to claim.

If types were observable, the principal would calculate the optimal time structure of benefits given $\omega = \omega_l$ and offer it only to the low types, ignoring the high types. Given unobservable search costs, however, there are two possible contracts the principal could offer: On the one hand, she could offer a pooling contract, which is accepted by both types, even though only one type needs insurance. On the other hand, she could offer a separating contract, which is designed in such a way that only the low types want to claim it. Importantly, there are always (ω_l, ω_h) so that the optimal contract under observable types cannot be implemented as a separating equilibrium under unobservable types, as demonstrated in the following lemma:

Lemma 3. *If $N(\omega) - \bar{V}$ is not too large, the optimal contract under observable types cannot be implemented as a separating equilibrium under unobservable types.*

Proof. Denote by $z^*(0), z^*(1)$ the optimal net transfers under observable types. Under optimality the promised utility constraint must be binding, since otherwise the transfers could be lowered, yielding lower costs, while still satisfying the constraint. This implies:

$$T(z^*(0), z^*(1), \omega_l) = \bar{V} + \psi$$

The high type prefers this contract to autarky if

$$T(z^*(0), z^*(1), \omega_h) \geq N(\omega_h) + \psi.$$

Combining both conditions, we find that this is the case if

$$T(z^*(0), z^*(1), \omega_h) - T(z^*(0), z^*(1), \omega_l) = \frac{1}{2}\left(\frac{1}{\omega_h} - \frac{1}{\omega_l}\right)(\log(\ell + z^*(1)))^2 \quad \geq \quad N(\omega_h) - \bar{V}.$$

Since $N(\omega)$ can be arbitrarily close to $\bar{V}$ while ω_l could be arbitrarily large, we can always find (ω_l, ω_h) such that the condition is fulfilled. But this means that the high types will also opt into the contract, meaning it is not implementable as a separating equilibrium. □

Separating contract. This means that the presence of optimal take-up affects the design of the separating contract. The principal faces the additional constraint of having the high types self-select into non-registered unemployment. The principal hence minimizes the expected cost of providing insurance, subject to the constraints that the low types achieve the minimum promised utility, the high types prefer not to claim, and that the low types choose search effort optimally:

$$\min_{z(0), z(1), e_l} \; z(0) + (1 - e_l) z(1)$$

$$\begin{aligned}
\text{s. t.} \quad &(\text{i}) \quad \log(\ell + z(0)) + (1 - e_l)\log(\ell + z(1)) - \frac{\omega_l}{2} e_l^2 \geq \bar{V} + \psi \\
&(\text{ii}) \quad \log(\ell + z(0)) + (1 - e_h)\log(\ell + z(1)) - \frac{\omega_h}{2} e_h^2 \leq N(\omega_h) + \psi \\
&(\text{iii}) \quad \omega_l e_l = -\log(\ell + z(1)),
\end{aligned}$$

where e_l and e_h denote search effort if registered of the low and high type, respectively. Denote by λ_0, λ_1 and μ the multipliers on the first, second, and third constraint, respectively. Moreover, note that the first-order conditions imply $e_h = (\omega_l/\omega_h)e_l > e_l$. The first-order conditions of the principal's problem are then

$$\ell + z(0) = \lambda_0 - \lambda_1 \tag{2.12}$$

$$\ell + z(1) = \lambda_0 - \lambda_1 \frac{1 - (\omega_l/\omega_h)e_l}{1 - e_l} - \mu \frac{1}{1 - e_l} \tag{2.13}$$

$$\mu = z(1)/\omega_l \tag{2.14}$$

$$\lambda_0 \geq 0, \lambda_1 \geq 0, \tag{2.15}$$

along with the usual complementary slackness conditions. Combining (2.12) and (2.13), we obtain

$$z(1) = z(0) - \underbrace{\mu \frac{1}{1 - e_l}}_{\text{Moral-hazard effect}} + \underbrace{\lambda_1 \frac{e_h - e_l}{1 - e_l}}_{\text{Take-up effect}}. \tag{2.16}$$

As a benchmark, consider the case of perfect information. This means that the principal can ignore the second constraint (as search costs are observable) and the third constraint (as search effort is observable), meaning $\lambda_1 = \mu = 0$. We then directly find $z(0) = z(1)$, i.e. the low types are perfectly insured against income fluctuations. In next step, assume now that search effort is not observable, while search costs are observable, in which case only $\lambda_1 = 0$. From (2.14) it follows that $\mu > 0$ whenever $z(1) > 0$, and hence from (2.16) $z(0) > z(1)$. This corresponds to the classical Shavell-Weiss result. Note that this result also applies if search costs are not observable but $N(\omega_h)$ is large, meaning that the second constraint does not bind.

If the autarky value of the high type is sufficiently small, however, the second constraint is binding and $\lambda_1 > 0$. We see from (2.16) that $z(1)$ tends to increase relative to $z(0)$, possibly overturning the usual effect due to moral hazard. The intuition is that the principal has to grant the promised utility to the low type, while not giving too much utility from claiming to the high type. This is done by backloading the schedule, since the low type values benefits in the second period more than the high type as he is more likely to remain unemployed.

Pooling equilibrium. Whenever the second constraint is binding, the separating equilibrium works by backloading the benefit scheme and thus making UI less attractive for the high type. However, making benefits less smooth over time also entails a utility cost for the low types. As their utility has to achieve the initially promised level, the principal has to compensate them by increasing the benefit level. But this means that providing insurance becomes more expensive compared to the case where the types are known, as implementing the separation is costly.

Hence, pooling, i.e. providing insurance to both types, could be a less costly alternative. While this means that insurance has to be paid to more people, the principal no longer has to separate types which entails costs. This alternative could be preferable in particular if the fraction of low types is very high. Since it is not as interesting as the separating case, I characterize the optimal pooling contract in Appendix C. It turns out that there are again two opposing forces. While on the one hand, moral hazard tends to lead to a downward-sloping schedule, the fact that typically only the low type's constraint is binding tends to push benefits upward over time. Importantly, as the share of low types approaches 1, the pooling contract approaches the Shavell-Weiss contract.

Numerical example. A small numerical example should be helpful in gaining an intuition for the previous results. Assume $(\omega_h, \omega_l) = (1, 2)$, $\ell = 0.72$, $\psi = 0.1$, and $q \equiv q(\omega_l) = 0.8$. This implies $N(\omega_l) = -0.63$ and $N(\omega_h) = -0.6031$. To make the problem interesting, I assume $\bar{V} = -0.62$, so that the low type has to be insured.

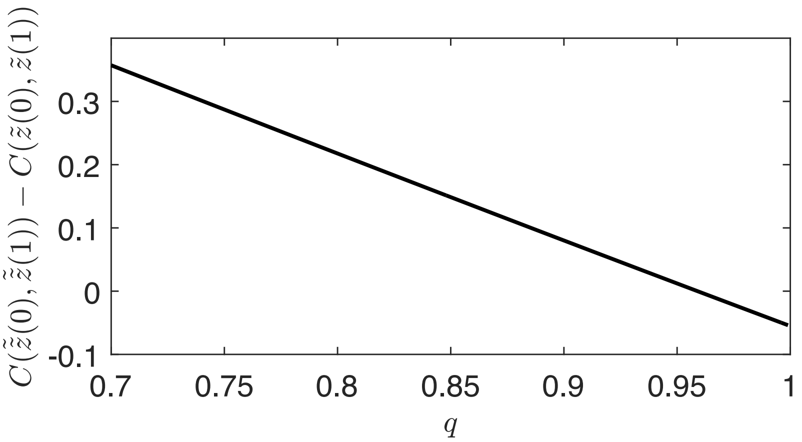


Figure 2.12: Cost of pooling contract minus cost of separating contract according to the share of low types

Under observable types, we can calculate the optimal benefit schedule by setting $\lambda_1 = 0$ in (2.12) to (2.14). This yields $(\ell + z^*(0), \ell + z^*(1)) = (0.9651, 0.5689)$. However, $T(z^*(0), z^*(1), \omega_h) = -0.4405 > N(\omega_h) + \psi$ and hence the high types would take-up UI as well. The optimal separating contract reads $(\ell + \tilde{z}(0), \ell + \tilde{z}(1)) = (0.7584, 0.7708)$. Strikingly, while the contract under observable types was strongly downward sloping, the separating contract is now weakly upward sloping. The pooling contract, on the other hand, can be calculated as $(\ell + \tilde{\tilde{z}}(0), \ell + \tilde{\tilde{z}}(1)) = (0.9660, 0.5682)$ and hence almost coincides with the solution under observable types. However, $C(\tilde{\tilde{z}}(0), \tilde{\tilde{z}}(1)) = 1.3607$ while $C(\tilde{z}(0), \tilde{z}(1)) = 1.1430$. Thus, the principal will implement the separating contract.

More generally, the principal will opt for the separating contract as long as the share of high types is not very low. In Figure 2.12, I plot $C(\tilde{\tilde{z}}(0), \tilde{\tilde{z}}(1)) - C(\tilde{z}(0), \tilde{z}(1))$, i.e. the cost of providing a pooling contract minus the cost of providing a separating contract depending on the share of low types, q. It turns out that for $q \geq 0.9590$, pooling becomes optimal.

2.6.4 General Case

While the previous setting is instructive to understand the general mechanism, we need to make the setting more general to get a realistic idea of the quantitative impact of the take-up channel. This is achieved by solving the model with many periods using calibrated parameter values.

Recursive formulation. In the following, I will assume that the population share of high types is sufficiently large so that pooling is not optimal. I will hence only characterize the separating contract. In the general case with many periods, the optimal separating contract solves the following program:

$$C_0(\bar{V}+\psi, N(\omega_h)+\psi) = \min_{\{z(t)\}_{t=0}^{T}} z(0) + \sum_{t=1}^{T} \delta^t \prod_{\tau=0}^{t-1}(1-e(\omega_l,\tau))z(t)$$

$$\begin{aligned} \text{s. t.} \quad & \text{(i)} \quad T(0;\omega_l) \geq \bar{V}+\psi \\ & \text{(ii)} \quad T(0;\omega_h) \leq N(\omega_h)+\psi \\ & \text{(iii)} \quad \text{Low types choose optimal } e(\omega_l,t) \text{ for all } t \text{ given } \{z(t)\}_{t=0}^{T}. \end{aligned}$$

Constraint (i) denotes the promised utility constraint, positing that the utility from claiming UI net of take-up costs to the low type be at least $\bar{V}$. Constraint (ii), on the other hand, is an incentive constraint, requiring that the high type's utility from claiming net of take-up costs do not exceed his utility in the non-registered state. Eventually, constraint (iii) is the usual incentive compatibility constraint acknowledging that workers choose optimal search effort. $C_0(\bar{V}+\psi, N(\omega_h)+\psi)$ is the minimized cost of providing insurance to the low types, given that low types receive at least $\bar{V}+\psi$ and the high types' value from claiming does not exceed $N(\omega_h)+\psi$. Note that, given the assumptions, constraint (i) will always be binding. Constraint (ii), on the other hand, can be slack: If the high type's outside value is very high, he does not have an incentive to claim even if the principal offers the Shavell-Weiss contract to the low types. Since the Shavell-Weiss contract cannot be improved upon, relaxing constraint (ii) will then not have any effect on $C_0(\bar{V}+\psi, N(\omega_h)+\psi)$.

This problem is numerically very hard to solve, as it involves searching over $T+1$ values, taking into account how optimal search effort reacts, and satisfying two nonlinear constraints. Fortunately, the problem can be simplified considerably by rewriting it recursively. For this purpose, define $C_t(V_t^l, V_t^h)$ to be the minimized cost of providing insurance *starting in period t*, given that low types receive at least value V_t^l and the high types' value does not exceed value V_t^h from period t onward. Clearly, we obtain the full problem as a special case of this definition by setting $t=0$ and $(V_t^l, V_t^h) = (\bar{V}+\psi, N(\omega_h)+\psi)$.

For all even nonterminal[9] periods, $C_t(V_t^l, V_t^h)$ satisfies the recursive relationship

$$C_t(V_t^l, V_t^h) = \min_{z(t),z(t+1),V_{t+2}^l,V_{t+2}^h} \left\{z(t) + \delta(1-e_l(t))\left\{z(t+1)+\delta(1-e_l(t+1))C_{t+2}(V_{t+2}^l, V_{t+2}^h)\right\}\right\}$$

[9]For the terminal period $T-1$, continuation values , V_{t+2}^l, V_{t+2}^h are fixed at $N(\omega_l)$ and $N(\omega_h)$ and we only minimize over $z(T-1)$ and $z(T)$.

$$\text{s. t.}\quad \text{(i)}\quad u(\ell+z(t))-\frac{\omega_l}{1+\kappa}e_l(t)^{1+\kappa}+\delta(1-e_l(t))\left\{u(\ell+z(t+1))-\frac{\omega_l}{1+\kappa}e_l(t+1)^{1+\kappa}+\delta(1-e_l(t+1))V^l_{t+2}\right\}\geq V^l_t$$

$$\text{(ii)}\quad u(\ell+z(t))-\frac{\omega_h}{1+\kappa}e_h(t)^{1+\kappa}+\delta(1-e_h(t))\left\{u(\ell+z(t+1))-\frac{\omega_l}{1+\kappa}e_h(t+1)^{1+\kappa}+\delta(1-e_h(t+1))V^h_{t+2}\right\}\leq V^h_t$$

$$\text{(iii)}\quad \omega_l e_l(t)^\kappa=-\delta\left\{u(\ell+z(t+1))-\frac{\omega_l}{1+\kappa}e_l(t+1)^{1+\kappa}+\delta(1-e_l(t+1))V^l_{t+2}\right\}$$

$$\text{(iv)}\quad \omega_h e_h(t)^\kappa=-\delta\left\{u(\ell+z(t+1))-\frac{\omega_h}{1+\kappa}e_h(t+1)^{1+\kappa}+\delta(1-e_h(t+1))V^h_{t+2}\right\}$$

$$\text{(v)}\quad \omega_l e_l(t+1)^\kappa=-\delta V^l_{t+2}$$

$$\text{(vi)}\quad \omega_h e_h(t+1)^\kappa=-\delta V^h_{t+2}.$$

That is, if we know the minimized cost of providing insurance from period $t+2$ onwards, granting at least value V^l_{t+2} to the low type and at most V^h_{t+2} to the high type, we can solve for the minimized cost of providing insurance from period t onwards, granting at least value V^l_t to the low type and at most V^h_t to the high type, by choosing the optimal combination of benefits in period t and $t+1$ as well as continuation values V^l_{t+2} and V^h_{t+2}, given the constraints that (i) the low types receive at least value V^l_t, (ii) the high types' value does not exceed V^h_t, and each type in each period chooses search effort optimally ((iii) - (vi)). Importantly, while in each period t we assume that agents cannot enter into the contract later on, providing insurance from period t onwards is equivalent to a sequence of recursive problems in all even periods after t, where the initial values (V^l_t, V^h_t) are determined endogenously. The reason that we solve for the benefit levels in t and $t+1$ at once is that by only choosing $z(t)$, we cannot choose continuation value V^l_{t+1} independently from V^h_{t+1}. Lastly, in order to solve for the optimal separating contract, we add the initial conditions $V^l_0=\bar{V}+\psi$ and $V^h_0=N(\omega_h)+\psi$.

Model solution. The usual strategy of solving this type of model involves forming a grid over the state variables and a starting guess for the cost function at each grid point. One then eliminates $z(t)$, $z(t+1)$, $e_l(t)$, and $e_l(t+1)$ from the objective function using the constraints. Using a numerical optimizer, one then minimizes the objective function at every grid point with respect to the continuation values $(V^l(t+2), V^h(t+2))$. This also requires interpolation of the cost function, typically by Chebychev polynomials. One then iterates on this procedure until convergence.

For several reasons, this standard procedure is hard to implement here. On the one hand, the implementation of Chebychev polynomials requires a rectangular state space, i.e. $(V^l_t, V^h_t)\in[\underline{V}^l,\overline{V}^l]\times[\underline{V}^h,\overline{V}^h]$. However, it turns out that the set of promised values (V^l_t, V^h_t) than can be generated by future transfers is not rectangular, but lens-shaped (see Figure 2.13). Interpolation techniques that allow interpolating over these domains, such as Delaunay triangulation, will generate a non-smooth surface which makes it very hard for numerical optimizers to converge. Also, the bounds of the state space is curved,

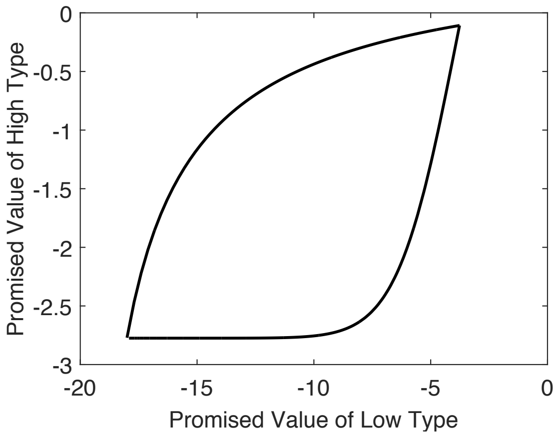


Figure 2.13: Example: feasible state space

which makes it hard to interpolate points at the bound even by triangulation.

To sidestep these issues, I apply the method of endogenous gridpoints first proposed by Carroll (2006). The solution algorithm works as follows:

Algorithm 2.1.

1. *Form an initial guess for the terminal states* (V_T^l, V_T^h)*. As both types are in non-registered unemployment from* $t = T + 2$*, we can solve for* $z(T)$ *and* $z(T+1)$ *from a simple system of equations. Calculate the envelope conditions* $\left(\frac{\partial C_T(\cdot)}{\partial V_T^l}, \frac{\partial C_T(\cdot)}{\partial V_T^h}\right)$.

2. *Given that we arrive in* (V_T^l, V_T^h)*, where did we have to originate in* $T-2$ *in order to* optimally *arrive there? Given* (V_T^l, V_T^h) *and the envelope conditions* $\left(\frac{\partial C_T(\cdot)}{\partial V_T^l}, \frac{\partial C_T(\cdot)}{\partial V_T^h}\right)$*, there are* analytical *expressions for the associated controls* $z(T-2)$ *and* $z(T-1)$*. Using the constraints, calculate states* (V_{T-2}^l, V_{T-2}^h)*, as well as the envelope conditions.*

3. *Repeat the previous step until arriving in* $t = 0$*. Compare* (V_0^l, V_0^h) *to the initial conditions.*

4. *Repeat all previous steps, searching over terminal states* (V_T^l, V_T^h)*, until the difference between* (V_0^l, V_0^h) *and the initial conditions meets an exit criterion.*

There are several advantages to this solution method compared to the traditional strategy: First, there is no need for numerical optimization, which can be very time-consuming (note that one needs to optimize separately for every point in the grid), and can have problems converging. Also, there is no need for interpolation, which naturally implies an approximation error. The choice of the interpolating function is somewhat arbitrary and can affect the results. Eventually, the strategy proposed here converges to the solution much more quickly. The disadvantage is that we need to assume that benefits are only paid up to period $T+1$, which, as pointed out above, is of little importance as T can be arbitrarily large[10].

In the following proposition, I derive the expressions for the optimal controls given the subsequent states and the envelope conditions.

Proposition 2.6. *Given envelope conditions* $\left(\frac{\partial C_{t+2}(\cdot)}{\partial V^l_{t+2}}, \frac{\partial C_{t+2}(\cdot)}{\partial V^h_{t+2}}\right)$*, whenever all constraints bind, optimal transfers* $(z(t), z(t+1))$ *satisfy*

$$\begin{aligned}\frac{1}{u'(\ell+z(t))} =& \frac{\partial C_{t+2}(\cdot)}{\partial V^l_{t+2}} + \frac{(1-e_l(t))(1-e_l(t+1))}{(1-e_h(t))(1-e_h(t+1))}\frac{\partial C_{t+2}(\cdot)}{\partial V^h_{t+2}} + \frac{\delta}{\omega_l \kappa}C_{t+2}(\cdot)\frac{e_l(t+1)^{1-\kappa}}{1-e_l(t+1)} \\ &+ \frac{\delta}{\omega_l\kappa}C_{t+1}(\cdot)\frac{e_l(t)^{1-\kappa}}{1-e_l(t)} \qquad (2.17)\\ \frac{1}{u'(\ell+z(t+1))} =& \frac{\partial C_{t+2}(\cdot)}{\partial V^l_{t+2}} + \frac{1-e_l(t+1)}{1-e_h(t+1)}\frac{\partial C_{t+2}(\cdot)}{\partial V^h_{t+2}} + \frac{\delta}{\omega_l\kappa}C_{t+2}(\cdot)\frac{e_l(t+1)^{1-\kappa}}{1-e_l(t+1)}. \qquad (2.18)\end{aligned}$$

The envelope conditions are calculated as

$$\begin{aligned}\frac{\partial C_t(\cdot)}{\partial V^l_t} =& \frac{1-e_l(t)}{e_h(t)-e_l(t)}\left(\frac{1}{u'(\ell+z(t+1))} + \frac{\delta}{\omega_l\kappa}C_{t+1}(\cdot)\frac{e_l(t)^{1-\kappa}}{1-e_l(t)}\right) - \frac{1-e_h(t)}{e_h(t)-e_l(t)}\frac{1}{u'(\ell+z(t))} \qquad (2.19)\\ \frac{\partial C_t(\cdot)}{\partial V^h_t} =& -\frac{1-e_l(t)}{e_h(t)-e_l(t)}\left(\frac{1}{u'(\ell+z(t+1))} + \frac{\delta}{\omega_l\kappa}C_{t+1}(\cdot)\frac{e_l(t)^{1-\kappa}}{1-e_l(t)} - \frac{1}{u'(\ell+z(t))}\right). \qquad (2.20)\end{aligned}$$

Proof. See appendix. □

To make sense of these results, it is useful to derive the same equations for the model where types are observable or where the incentive constraint does not bind, i.e. for the Shavell-Weiss contract.

Lemma 4. *If types are observable or if the incentive constraint of high types does not bind, optimal benefits over time satisfy*

$$\frac{1}{u'(\ell+z(t))} = \frac{1}{u'(\ell+z(t+1))} + \frac{\delta}{\omega_l\kappa}C_{t+1}(\cdot)\frac{e_l(t)^{1-\kappa}}{1-e_l(t)}. \qquad (2.21)$$

Proof. See appendix. □

---

[10]Note that the method of endogenous gridpoints in principle allows for infinite horizon problems. However, this would require Delaunay interpolation, which, as explained above, is very difficult – if feasible at all – given the irregular state space.

Comparison of this result with the envelope condition (2.20) directly implies that, using $u''(c) < 0$, $\frac{\partial C_t(\cdot)}{\partial V_t^h} < 0$ as long as $z(t+1)$ relative to $z(t)$ is higher than implied by the Shavell-Weiss contract: If we have not yet reached the cost-minimizing contract under observable types, cost would decrease as the constraint becomes less strict. As soon as $\frac{\partial C_t(\cdot)}{\partial V_t^h}$ becomes zero, no further cost savings are possible by changing $z(t)$ relative to $z(t+1)$, as the principal already offers the cost-minimizing contract under observable types. $\frac{\partial C_t(\cdot)}{\partial V_t^l}$, on the other hand, approaches $1/u'(\ell + z(t))$ from above, which corresponds to the envelope condition under observable types. It can then be verified that equations (2.17) and (2.18) reduce to equation (2.21), meaning that the problem reduces to the standard problem.

Moreover, combining equations (2.17) and (2.18) implies

$$\frac{1}{u'(\ell + z(t))} = \frac{1}{u'(\ell + z(t+1))} + \underbrace{\frac{\delta}{\omega_l \kappa} C_{t+1}(\cdot) \frac{e_l(t)^{1-\kappa}}{1 - e_l(t)}}_{\text{Moral-hazard effect}>0} + \underbrace{\frac{1 - e_l(t+1)}{1 - e_h(t+1)} \frac{e_h(t) - e_l(t)}{1 - e_h(t)} \frac{\partial C_{t+2}(\cdot)}{\partial V_{t+2}^h}}_{\text{Take-up effect}\leq 0},$$

which differs from equation (2.21) by the take-up effect. We can directly conclude that, if the incentive constraint for the high types binds in $t+2$ ($\frac{\partial C_{t2+}(\cdot)}{\partial V_{t+2}^h} < 0$), it will continue to do so in t, as the principal will choose $z(t)$ lower relative to $z(t+1)$ compared to the Shavell-Weiss contract. The conclusion is that the incentive constraint either binds for all periods or never. In particular, if the principal has to deviate from the Shavell-Weiss contract, the resulting contract will be more positively or less negatively sloped than the Shavell-Weiss contract everywhere.

Calibration. One period is chosen to be one week. I assume that utility is CRRA, i.e. $u(c) = c^{1-\gamma}/(1-\gamma)$ and assume $\gamma = 1$. Moreover, I assume that consumption in autarky ℓ is two thirds of the average wage. This is a fairly innocuous assumption as it will only scale the optimal benefit schedule up or down and just needs to be fixed in order to obtain the values in autarky. The elasticity of marginal search costs, κ, and the discount rate, δ, are set to the same value as in Table 2.3.

The parameters (ω_l, ω_h) have to be chosen in a way that approximates a continuous distribution. Since with continuous types the promised utility constraint will always bind for the lowest type, ω_l should be chosen to approximate the lowest type actively searching for a job. The incentive constraint, on the other hand, will always bind for the marginal type excluded from UI. Hence, ω_h should be set to the value of the lowest type not claiming UI. Based on these considerations, I calibrate (ω_l, ω_h) to obtain an average duration of nonemployment in the non-registered state of 30 and 3 weeks, respectively. T should be chosen to be very high compared to the average nonemployment spell. In practice $T = 156$

weeks turns out to be sufficient. The resulting calibration is summarized in Table 2.6.

Parameter	Definition	Value
ω_l	Search cost param. low type	548.076
ω_h	Search cost param. high type	12.480
ℓ	Consumption in autarky	0.667
κ	Elasticity of marg. search cost	1.000
δ	Discount rate	0.999
γ	Coefficient of relative risk aversion	1.000
T	Time Horizon	156

Table 2.6: Baseline calibration

Optimal benefit schedules. To explore the effects for optimal benefits over time, I set $\bar{V}$ equal to the value a low type would obtain if receiving a flat benefit at 20% of the average wage. This is a reasonable assumption, as this is the average level of benefits paid for 156 weeks, while benefits are typically only granted for about six to twelve months. I then calculate the optimal separating contract for different levels of the take-up cost ψ. For better interpretability, I convert ψ to the equivalent relative income loss Δ in monetary units, which solves

$$u(\ell) - \psi = u((1 - \Delta)\ell).$$

For a very high take-up cost, high types won't have an incentive to claim UI even if the Shavell-Weiss, i.e. unconstrained, contract is offered to low types. It turns out that the principal will offer this contract for Δ above 95%. For all Δ below this value, the principal will have to backload the schedule relative to the Shavell-Weiss contract to keep high types from selecting into the contract.

In Figure 2.14, I plot the Shavell-Weiss contract, corresponding to the optimal contract for Δ equal to 95%, in red. In black, on the other hand, I plot the optimal contract if take-up costs are lowered to 60% of weekly consumption. While these take-up costs are arguably still very high, the contract is distorted considerably. The difference is especially marked during the initial weeks, where benefit is considerably lower. This is compensated by higher benefits later on[11]. Moreover, while initially the take-up effect dominates and the schedule becomes upward sloping, later on the moral-hazard effect dominates leading to a downward sloping schedule. However, one has to keep in mind that the results are

[11]The comparison in levels is partly misleading as higher take-up costs have to be compensated by a higher level of benefits later on. Hence, the red line is shifted upward to fulfill the initial promise constraint.

always relative to the benchmark with no savings. As mentioned before, allowing for savings will lead to more backloading even in the case with observable types.

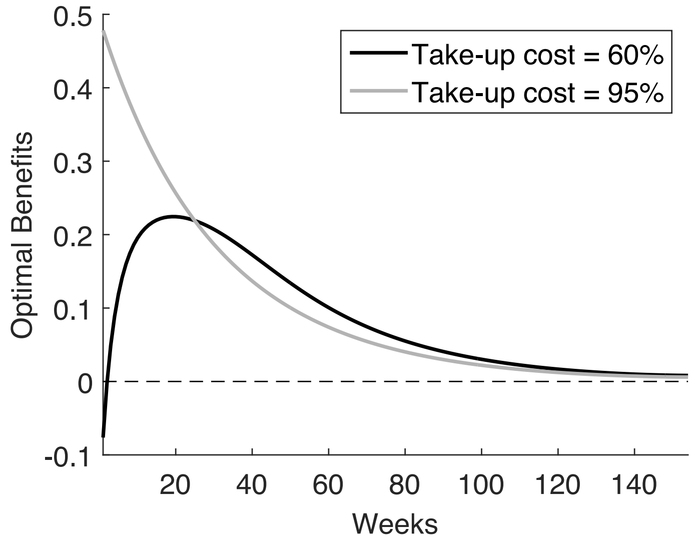


Figure 2.14: Optimal benefit schedules

The Shavell-Weiss result has often been quoted as a reference to justify the usual practice of a constant benefit to be paid for a finite duration. The real-world implication of the result allowing for take-up, on the other hand, would make a case for increasing benefits, at least at the beginning of the spell, and a longer maximum benefit duration. One way of implementing this would by way of a mandatory waiting period before receiving benefits.

2.7 Conclusion

I proceeded from a puzzling but still quite robust and widely documented empirical fact: Even though entitled to do so, many unemployed deliberately choose not to claim UI benefits. This finding stands in stark contrast to the assumptions commonly made in macro models, where the take-up rate is assumed to be 100%. This assumption might be innocuous if take-up can be regarded as an isolated phenomenon, not interacting with the labor market aggregates. The goal of this paper was to demonstrate the opposite – that take-up behavior can affect the equilibrium in a labor market in a qualitatively and quantitatively important way by interacting with search effort.

On the one hand, this interaction manifests itself along the business cycle: Conditional on the past take-up decision, search incentives for the registered are lower than for the non-registered. Since more workers claim unemployment insurance during downturns, this leads to amplification in fluctuations in search effort, and thus also in unemployment and vacancies. Indeed, a simulation of the model calibrated to match long-term averages in take-up and job-finding rates demonstrates that the effect of the channel is quantitatively important, more than doubling the volatility of search effort while increasing the volatility of the labor market aggregates by 15 to 30%. In addition, the model also matches empirical patterns fairly well, as was demonstrated by a simulation of historical data.

The model's predictions along the business cycle might also be important for policy-makers. First, the current share of the unemployed on benefits might be an important indicator of how extended a period of high unemployment is. Also, since workers endogenously sort into registered unemployment, the composition of the registered unemployed might be very different at different points of the cycle. This can have important consequences for the optimal design of unemployment insurance, since the registered unemployed respond differently to incentives at different points in time. Interestingly, the finding that UI can amplify fluctuations if there is variable take-up contrasts with its traditional role as an automatic stabilizer[12].

On the other hand, endogenous UI take-up also has important implications in the steady state: The specific design of the UI contract will affect workers' decision to claim. Governments can save money by designing the contract in a way that keeps workers that do not need to be insured from claiming. This is generally achieved by backloading the schedule, working against the classical result that UI benefits should be decreasing over time.

Even though many aspects of UI take-up have been covered in this paper, there are many important questions that remain unanswered: As a first example, I completely abstracted from savings motives in this paper, while an interesting question is also how take-up interacts with workers' assets. Also, take-up costs were always taken as given. However, as they could be partly controlled by the government, one should also explore whether there is an optimal level of the take-up cost and whether they are generally too low or too high. These are only two examples of a long list of topics in a field that has received little attention so far.

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[12] I am grateful to Pierre Cahuc for pointing out this aspect to me.

2.8 Appendix

A Estimating Job Separations from CPS Data

This section details the methodology proposed by Shimer (2005b) to estimate job-finding rates f_t and separations rates λ_t during period t. I then use λ_t to get estimate the flow of separation between t and $t+1$, $S_{t,t+1}$.

The two critical assumptions are that movements in and out of the labor force can be ignored and that all unemployed workers find jobs at rate f_t while all workers lose their jobs at rate λ_t. The model presumes a continuous time environment in which data are measured at discrete dates $t \in \{0, 1, 2, \ldots\}$. Given some t, let $\tau \in [0, 1]$ denote the time elapsed since the previous measurement date. Further, denote by $e_{t+\tau}$ employment at time $t+\tau$, by $u_{t+\tau}$ the number of unemployed workers at $t+\tau$, and by $u^s_{t+\tau}$ as "short-term unemployment", workers who are unemployed at $t+\tau$ but where employed at least once since t.

For lack of within period data, assume that f_t and s_t are constant within periods. Then, unemployment and short-term unemployment satisfy the differential equations

$$\dot{u}_{t+\tau} = e_{t+\tau}\lambda_t - u_{t+\tau}f_t \tag{2.22}$$

and

$$\dot{u}^s_{t+\tau} = e_{t+\tau}\lambda_t - u^s_{t+\tau}f_t. \tag{2.23}$$

Subtracting (2.23) from (2.22) and rearranging, we find

$$\frac{\dot{(u_{t+\tau} - u^s_{t+\tau})}}{(u_{t+\tau} - u^s_{t+\tau})} = -f_t.$$

Using $u^s_t = 0$, this can be solved for u_{t+1} and u^s_{t+1} given u_t:

$$u_{t+1} = e^{-f_t}u_t + u^s_{t+1}. \tag{2.24}$$

Given data on unemployment and short-term unemployment, this equation can be used to determine the job-finding probability.

Moreover, using the assumption that the labor force $l_t = e_t + u_t$ is constant during period t, we can rewrite (2.22) to obtain

$$\dot{u}_{t+\tau} = l_t\lambda_t - (f_t + \lambda_t)u_{t+\tau}.$$

Given initial condition u_t, this differential equation has the solution

$$u_{t+1} = \frac{\left(1 - e^{-f_t - \lambda_t}\right)\lambda_t}{f_t + \lambda_t} l_t + e^{-f_t - \lambda_t} u_t,$$

which, given f_t determined in (2.24), pins down λ_t and can easily be solved numerically.

Given an estimate λ_t of the separation rate between t and $t+1$, the flow of job separations during period $[t, t+1)$ is given by

$$S_t = \int_0^1 \lambda_t e_{t+\tau}\, d\tau \approx \lambda_t \frac{e_t + e_{t+1}}{2},$$

where the approximation uses a linear interpolation of $e_{t+\tau}$ for $\tau \in (0,1)$.

The method is implemented using monthly data on employment and unemployment based on the CPS and published by the Bureau of Labor Statistics for e_t and u_t, respectively. Moreover, the BLS also publishes the number of unemployed with unemployment duration below five weeks, which is used for u_t^s.

B A Steady-State Model with Nash Bargaining

When a firm is matched to an unemployed worker, the wage is fixed by generalized Nash bargaining, solving

$$J_i = (1-\beta)(J_i + W_i - h_i T_i - (1-h_i)N_i),$$

where β is workers' bargaining power and where we have already used vacancies yield zero value in equilibrium. Once the wage w_i is fixed, I assume that it is not bargained anew. I thus rule out the (unrealistic) possibility that the wage is bargained anew once take-up costs are not sunk anymore. Call $S_i(h) \equiv J_i + W_i - hT_i - (1-h)N_i$ the surplus if a firm is matched to a worker who had registration status h before.

A firm matched to a worker with search costs ω_i earns value

$$(1-\delta)J_i = \exp(p) - w_i - \delta\lambda J_i. \tag{2.25}$$

Turning to the labor supply side, equations (2.5) to (2.7) simplify to

$$(1-\delta)N_i = \max_{e_i \geq 0}\left\{\ell - \frac{\omega_i}{1+\kappa}e_i^{1+\kappa} + \delta e_i f(\theta)(W_i - N_i)\right\}, \tag{2.26}$$

$$(1-\delta)T_i = \max_{e_i \geq 0}\left\{\ell + z - \frac{\omega_i}{1+\kappa}e_i^{1+\kappa} + \delta e_i f(\theta)(W_i - T_i)\right\}, \tag{2.27}$$

and

$$(1-\delta)W_i = w_i + \delta\lambda(U_i - W_i), \tag{2.28}$$

where $U_i = \max\{T_i - \psi, N_i\}$. The unemployed always make the same take-up decision upon becoming unemployed and the registration status is hence given by

$$h_i = k_i(p) = \mathbf{1}\left[T_i - \psi \geq N_i\right] = \mathbf{1}\left[\beta(S_i(0) - S_i(1)) - \psi \geq 0\right].$$

Steady-state optimal search effort for registered and non-registered unemployed, $e_i(1)$ and $e_i(0)$, are determined by the first-order conditions

$$\begin{aligned}\omega_i(e_i(1))^\kappa &= \delta f(\theta)(W_i - T_i) = \delta f(\theta)\beta S_i(1)\\ \omega_i(e_i(0))^\kappa &= \delta f(\theta)(W_i - N_i) = \delta f(\theta)\beta S_i(0).\end{aligned}$$

Call $e_i = e_i(h_i)$. Equilibrium unemployment follows as

$$u_i = \frac{\lambda}{\lambda + e_i f(\theta)}.$$

Combining equations (2.25) to (2.28) with the FOCs for search effort and the Nash bargaining assumption, one can show that the surplus functions solve

$$(1-\delta(1-\lambda))S_i(h) + \frac{\kappa}{1+\kappa}\omega_i^{-1/\kappa}(\delta f(\theta)\beta S_i(h))^{\frac{1+\kappa}{\kappa}} = p - \ell - h(z + \delta\lambda\psi).$$

I assume random search, meaning that firms cannot direct their search to specific types of workers. The value of a vacancy is hence independent of i and given by

$$V = -c + \delta q(\theta)\frac{\int_0^\infty e_i u_i (1-\beta) S_i(h_i)\, dF(\omega_i)}{\int_0^\infty e_i u_i\, dF(\omega_i)}.$$

Equilibrium labor market tightness solves the free-entry condition $V = 0$.

C Optimal Pooling Contract

The principal solves the following program:

$$\min_{z(0),z(1),e} z(0) + q(1-e_l)z(1) + (1-q)(1-e_h)z(1)$$

subject to

$$\begin{aligned}
\log(\ell + z(0)) + (1 - e_l)\log(\ell + z(1)) - \frac{\omega_l}{2}e_l^2 &\geq \bar{V} + \psi \\
\log(\ell + z(0)) + (1 - e_h)\log(\ell + z(1)) - \frac{\omega_h}{2}e_h^2 &\geq N(\omega_h) + \psi \\
\omega_h e_h &= -\log(\ell + z(1)) \\
\omega_l e_l &= -\log(\ell + z(1)),
\end{aligned}$$

where e_h and e_l denote the search effort levels of the high and low types, respectively.

Denote by λ_0, λ_1, μ_l, and μ_h the multipliers on the first, second, third, and fourth constraint, respectively. The first-order conditions of the principal's problem are then

$$\begin{aligned}
\ell + z(0) &= \lambda_0 + \lambda_1 \\
\ell + z(1) &= \frac{\lambda_0(1 - e_l) + \lambda_1(1 - e_h)}{q(1 - e_l) + (1 - q)(1 - e_h)} - (\mu_l + \mu_h)\frac{1}{q(1 - e_l) + (1 - q)(1 - e_h)} \\
\mu_l &= qz(1)/\omega_l \\
\mu_h &= (1 - q)z(1)/\omega_h \\
\lambda_0 &\geq 0, \lambda_1 \geq 0,
\end{aligned}$$

along with the usual complementary slackness conditions. By the same argument as before, if $\bar{V}$ is close enough to $N(\omega_h)$, the second constraint is slack. Hence, in solving the model we can guess $\lambda_1 = 0$ and verify that the solution satisfies the constraint.

Under this assumption, the FOC's imply

$$z(1) = z(0)\frac{1}{q + (1 - q)\frac{1 - e_h}{1 - e_l}} - z(1)\frac{q/\omega_l + (1 - q)/\omega_h}{q(1 - e_l) + (1 - q)(1 - e_h)}.$$

The second term pushes b_1 downward due to the usual moral hazard effect. The total effect is ambiguous, however, as the first term tends to push b_1 upward. The reason is that both types affect costs, while only the low type's constraint is binding. Importantly, the pooling contract converges to the Shavell-Weiss contract if $q \to 1$.

D Omitted Proofs

PROOF OF PROPOSITION 2.1:

By assumption, $p \in [\underline{p}, \overline{p}]$. Let $(\mathcal{B}(S), d_\infty)$ denote the space of all bounded, bounded away from zero, and continuous functions defined on state space $S = [\underline{p}, \overline{p}]$ equipped with the metric $d_\infty(f,g) = ||f-g||_\infty$ for some $f,g \in \mathcal{B}(S)$. The policy function $\theta(p)$ is the fixed point of the operator $T : \mathcal{B}(S) \to \mathcal{B}(S)$ defined by

$$\frac{c}{\delta q(T\theta(p))} = \mathbb{E}_p \left\{ \exp(p') - w(p') + (1-\lambda)\frac{c}{q(\theta(p))} \right\}.$$

By Banach's Fixed Point Theorem (see, e.g., Stachurski (2009)), since $(\mathcal{B}(S), d_\infty)$ is a complete metric space, T has a unique fixed point $\theta(p)$ if T is a uniform contraction on S.

To see that T is uniformly contracting, note that, for any $v, w \in \mathcal{B}(S)$, we have

$$\begin{aligned}
\left| \frac{c}{\delta q(Tv(p))} - \frac{c}{\delta q(Tw(p))} \right| &= \left| (1-\lambda)\mathbb{E}_p \left\{ \frac{c}{q(v(p))} - \frac{c}{q(w(p))} \right\} \right| \\
&\leq (1-\lambda)\mathbb{E}_p \left\{ \left| \frac{c}{q(v(p))} - \frac{c}{q(w(p))} \right| \right\} \\
\Leftrightarrow \left| \frac{1}{q(Tv(p))} - \frac{1}{q(Tw(p))} \right| &\leq \delta(1-\lambda)\mathbb{E}_p \left\{ \left| \frac{1}{q(v(p))} - \frac{1}{q(w(p))} \right| \right\} \\
&\leq \delta(1-\lambda)\mathbb{E}_p \left\{ \sup_p \left| \frac{1}{q(v(p))} - \frac{1}{q(w(p))} \right| \right\} \\
&= \underbrace{\delta(1-\lambda)}_{<1} \sup_p \left| \frac{1}{q(v(p))} - \frac{1}{q(w(p))} \right|.
\end{aligned}$$

Since $1/q(\cdot)$ is strictly increasing, we conclude

$$|Tv(p) - Tw(p)| < \sup_p |v(p) - w(p)| \ \forall p.$$

Taking the supremum over p on the left-hand side, we conclude

$$d_\infty(Tv, Tw) < d_\infty(v, w)$$

and hence T is uniformly contracting on S. Thus, $\theta(p)$ exists and is unique.

Define instantaneous profits $\pi(p) \equiv \exp(p) - w(p)$. Observe that

$$\pi'(p) = \exp(p) - (1-\gamma)w_0 \exp((1-\gamma)p) = \exp(p) - (1-\gamma)w(p) = \pi(p) + \gamma w(p) > 0,$$

as long as $\pi(p) > 0$. To prove monotonicity, since T is uniformly contracting, it suffices to show that T maps an arbitrary strictly increasing function $v(p)$ into a strictly increasing function $Tv(p)$. Since $1/q(\cdot)$ is monotonically increasing and $\exp(p) - w(p)$ is increasing, this is the case.

PROOF OF PROPOSITION 2.2:

In Proposition 2.1, it was shown that the policy function $\theta(p)$ exists and is unique under the given assumptions. Hence, I will continue to prove existence and uniqueness for the worker side.

Note that we can rewrite the worker problem (equations (2.5) to (2.7)) in one recursive equation. Define $U_i(p,s)$ as the value of the unemployed with search cost parameter ω_i and *last period* registration status s given productivity p. It is given by

$$\begin{aligned} U_i(p,s) = \max_{e_i \geq 0, s' \in \{0,1\}} \Big\{ & \ell + s'z - (1-s)s'\psi - \frac{\omega_i}{1+\kappa} e_i^{1+\kappa} \\ & + \delta \left[e_i f(\theta(p)) \mathbb{E}_p W_i(p') + (1 - e_i f(\theta(p)) \mathbb{E}_p U_i(p', s') \right] \Big\}, \end{aligned}$$

where the current registration status is now denoted by s'. In particular, take-up costs ψ only have to be borne if not yet registered ($s = 0$). As can easily be checked, this dynamic equation is equivalent to $(U_i(p), N_i(p), T_i(p))$. The value of a worker only has to rewritten slightly, accounting for the fact that a newly laid-off worker always has $s = 0$:

$$W_i(p) = w(p) + \delta \left[\lambda \mathbb{E}_p U_i(p', 0) + (1 - \lambda) \mathbb{E}_p W_i(p') \right]$$

Since $W_i(p)$ does not involve any worker choices, we might as well maximize $G_i(p,s) \equiv U_i(p,s) - W_i(p)$, given by

$$\begin{aligned} G_i(p,s) &= \max_{e_i \geq 0, s' \in \{0,1\}} \Big\{ \ell + s'z - (1-s)s'\psi - \frac{\omega_i}{1+\kappa} e_i^{1+\kappa} - w(p) \\ &+ \delta\lambda \mathbb{E}_p \left(U_i(p', s') - U_i(p', 0) \right) + \delta(1 - \lambda - e_i f(\theta(p)) \mathbb{E}_p G_i(p', s') \Big\} \\ &= \max_{e_i \geq 0, s' \in \{0,1\}} \Big\{ u_i(s, s', e, p) + \delta\lambda \mathbb{E}_p \left(G_i(p', s') - G_i(p', 0) \right) \\ &+ \delta(1 - \lambda - e_i f(\theta(p)) \mathbb{E}_p G_i(p', s') \Big\}, \end{aligned}$$

where $u_i(s, s', e, p) \equiv \ell + s'z - (1-s)s'\psi - \frac{\omega_i}{1+\kappa} e_i^{1+\kappa} - w(p)$.

By assumption, $\omega_i \geq \underline{\omega}$, where $\underline{\omega}$ is such that $e_i \leq \overline{e}$, where $\max\{\overline{e} f(\theta(p))\} \leq 1 - \lambda$ and $p \in [\underline{p}, \overline{p}]$. Let $(\mathcal{B}(S), d_\infty)$ denote the space of all bounded and continuous functions defined on state space $S = [\underline{p}, \overline{p}] \times \{0,1\}$ equipped with the metric $d_\infty(f,g) = ||f - g||_\infty$ for some $f, g \in \mathcal{B}(S)$. Let $\mathcal{E} \equiv [0, \overline{e}] \times \{0,1\}$. The value function $G_i(p,s)$ is the fixed point of the Bellman operator $T : \mathcal{B}(S) \to \mathcal{B}(S)$ is defined by

$$Tw_i(p,s) = \max_{(e_i,s')\in\mathcal{E}} \Big\{ u_i(s,s',e,p) + \delta\lambda\mathbb{E}_p\left(w_i(p',s') - w_i(p',0)\right) \\ + \delta(1-\lambda-e_i f(\theta(p))\mathbb{E}_p w_i(p',s') \Big\} \ \forall (p,s)\in S.$$

By the Weierstrass Theorem, as $\mathcal{E}$ is compact and the objective function is bounded and continuous, a solution to the optimization problem always exists.

In order to prove existence and uniqueness, the following lemma will be important:

Lemma 5. *The Bellman operator T is uniformly contracting at rate $\delta(1-\lambda)$, that is, for $v, w \in \mathcal{B}(S)$,*

$$d_\infty(Tv, Tw) \leq \delta(1-\lambda) d_\infty(v,w).$$

Proof. For any $v, w \in \mathcal{B}(S)$ and any $(p,s)\in S$, we have

$$|Tw_i(p,s) - Tv_i(p,s)| = \\ \Bigg| \sup_{(e_i,s')\in\mathcal{E}} \Big\{ u_i(s,s',e,p) + \delta\lambda\mathbb{E}_p\left(w_i(p',s') - w_i(p',0)\right) + \delta(1-\lambda-e_i f(\theta(p))\mathbb{E}_p w_i(p',s') \Big\} \\ - \sup_{(e_i,s')\in\mathcal{E}} \Big\{ u_i(s,s',e,p) + \delta\lambda\mathbb{E}_p\left(v_i(p',s') - v_i(p',0)\right) + \delta(1-\lambda-e_i f(\theta(p))\mathbb{E}_p v_i(p',s') \Big\} \Bigg|,$$

and hence, using $|\sup w - \sup v| \leq \sup |w - v|$, defining $\Delta_{s'} \equiv \mathbb{E}_p\left(w_i(p',s') - v_i(p',s')\right)$, and suppressing the argument of $f(\cdot)$ for simplicity,

$$\begin{aligned} |Tw_i(p,s) - Tv_i(p,s)| &\leq \delta \sup_{(e_i,s')\in\mathcal{E}} \Big| (1-\lambda-e_i f)\Delta_{s'} + \lambda\left(\Delta_{s'} - \Delta_0\right) \Big| \\ &= \delta \sup_{(e_i,s')\in\mathcal{E}} \Big| (1-e_i f)\Delta_{s'} - \lambda\Delta_0 \Big| \\ &= \delta \max\Big\{ \sup_{e_i\in[0,\bar{e}]} \Big| (1-\lambda-e_i f)\Delta_0 \Big|, \\ &\qquad \sup_{e_i\in[0,\bar{e}]} \Big| (1-e_i f)\Delta_1 - \lambda\Delta_0 \Big| \Big\}. \end{aligned}$$

Focusing on the second part of the max-operator, observe that, as by assumption $e_i f < 1-\lambda$,

$$\Delta_1 \geq \Delta_0 \Rightarrow (1-\lambda-e_i f)\Delta_0 \leq (1-e_i f)\Delta_1 - \lambda\Delta_0 \leq (1-\lambda-e_i f)\Delta_1,$$

while

$$\Delta_0 > \Delta_1 \Rightarrow (1-\lambda-e_i f)\Delta_1 < (1-e_i f)\Delta_1 - \lambda\Delta_0 < (1-\lambda-e_i f)\Delta_0.$$

Thus,

$$\sup_{e_i\in[0,\bar{e}]}\Big|(1-e_if)\Delta_1-\lambda\Delta_0\Big| \leq \max\left\{\sup_{e_i\in[0,\bar{e}]}\Big|(1-\lambda-e_if)\Delta_1\Big|,\ \sup_{e_i\in[0,\bar{e}]}\Big|(1-\lambda-e_if)\Delta_0\Big|\right\}$$

and

$$\begin{aligned}
|Tw_i(p,s)-Tv_i(p,s)| &\leq \delta\max\left\{\sup_{e_i\in[0,\bar{e}]}\Big|(1-\lambda-e_if)\Delta_0\Big|,\right.\\
&\qquad \left.\max\left\{\sup_{e_i\in[0,\bar{e}]}\Big|(1-\lambda-e_if)\Delta_1\Big|,\ \sup_{e_i\in[0,\bar{e}]}\Big|(1-\lambda-e_if)\Delta_0\Big|\right\}\right\}\\
&= \delta\max\left\{\sup_{e_i\in[0,\bar{e}]}\Big|(1-\lambda-e_if)\Delta_0\Big|,\ \sup_{e_i\in[0,\bar{e}]}\Big|(1-\lambda-e_if)\Delta_1\Big|\right\}\\
&= \delta\sup_{(e_i,s_i')\in\mathcal{E}}\Big|(1-\lambda-e_if)\Delta(s')\Big|\\
&\leq \delta(1-\lambda)\sup_{s_i'\in\{0,1\}}\Big|\mathbb{E}_p\left(w_i(p',s_i')-v_i(p',s_i')\right)\Big|\\
&\leq \delta(1-\lambda)\sup_{s_i'\in\{0,1\}}\mathbb{E}_p\left(\Big|w_i(p',s_i')-v_i(p',s_i')\Big|\right)\\
&\leq \delta(1-\lambda)\sup_{s_i'\in\{0,1\}}\mathbb{E}_p\left(\Big|\Big|w_i(p',s_i')-v_i(p',s_i')\Big|\Big|_\infty\right)\\
&= \delta(1-\lambda)||w_i-v_i||_\infty.
\end{aligned}$$

Taking the supremum over $|Tw_i(p,s)-Tv_i(p,s)|$ gives the desired inequality. □

By Banach's Fixed Point Theorem (see, e.g., Stachurski (2009)), since $(\mathcal{B}(S),d_\infty)$ is a complete metric space and T is a uniform contraction on S, T has a unique fixed point $G_i(p,s)$. Hence, an equilibrium exists and is unique.

PROOF OF LEMMA 2:

We have $U_i(p)=\max\{T_i(p)-\psi,N_i(p)\}<T_i(p)$ using Lemma 1. Claim (i) follows then directly from the two first-order conditions.

From the two first-order conditions, it is apparent that to show claim (ii), it suffices to show that $(W_i(p)-U_i(p))/\omega_i$ and $(W_i(p)-T_i(p))/\omega_i$ are decreasing in ω_i, or equivalently, that $(U_i(p)-W_i(p))/\omega_i$ and $(T_i(p)-W_i(p))/\omega_i$ are increasing in ω_i. Note that we showed in Theorem 2.2 that the recursive system is uniformly contracting given the stated assumptions. Hence, it suffices to show that the Bellman operator T, defined in the proof of Theorem 2.2, maps arbitrary increasing functions $(\tilde{N}_i(p)-\tilde{W}_i(p))/\omega_i,(\tilde{T}_i(p)-$

$\tilde{W}_i(p))/\omega_i$, and $(\tilde{U}_i(p)-\tilde{W}_i(p))/\omega_i$ into increasing $(\tilde{\tilde{N}}_i(p)-\tilde{\tilde{W}}_i(p))/\omega_i$, $(\tilde{\tilde{T}}_i(p)-\tilde{\tilde{W}}_i(p))/\omega_i$, and $(\tilde{\tilde{U}}_i(p)-\tilde{\tilde{W}}_i(p))/\omega_i$. To see this, note that since $\omega_i>0$, the recursive system can be rewritten and the Bellman operator implies

$$\frac{\tilde{\tilde{N}}_i(p)-\tilde{\tilde{W}}_i(p)}{\omega_i}=\max_{e_i\geq 0}\left\{\frac{\ell-w(p)}{\omega_i}-\frac{1}{1+\kappa}e_i^{1+\kappa}+\delta(1-\lambda-e_i f(\theta(p)))\mathbb{E}_p\left(\frac{\tilde{U}_i(p)-\tilde{W}_i(p)}{\omega_i}\right)\right\}$$

and

$$\frac{\tilde{\tilde{T}}_i(p)-\tilde{\tilde{W}}_i(p)}{\omega_i}=\max_{e_i\geq 0}\left\{\frac{\ell+z-w(p)}{\omega_i}-\frac{1}{1+\kappa}e_i^{1+\kappa}+\delta(1-\lambda-e_i f(\theta(p)))\mathbb{E}_p\left(\frac{\tilde{T}_i(p)-\tilde{W}_i(p)}{\omega_i}\right)\right\}.$$

Consider a change of ω_i to $\omega_j>\omega_i$ but keep search effort fixed at e_i^*, where e_i^* denotes the maximizer given ω_i in the respective equation. By assumption, the terms in expectations will increase for every p, leading to an increase in the expectations. Also, since $\ell+z-w(p)<0$ and $\ell-w(p)<0$, $\frac{\ell-w(p)}{\omega_i}$ and $\frac{\ell+z-w(p)}{\omega_i}$ increase as well. When we change e_i^* to e_j^*, the value can be no smaller, since e_j^* is the maximizer. This establishes that $\tilde{\tilde{N}}_i(p)-\tilde{\tilde{W}}_i(p))/\omega_i$ and $\tilde{\tilde{T}}_i(p)-\tilde{\tilde{W}}_i(p))/\omega_i$ are increasing in ω_i as well, which then follows for $\tilde{\tilde{U}}_i(p)-\tilde{\tilde{W}}_i(p))/\omega_i$ directly. Hence, the same has to hold for $(U_i(p)-W_i(p))/\omega_i$ and $(T_i(p)-W_i(p))/\omega_i$, the fixed point of T, which establishes the claim.

PROOF OF PROPOSITION 2.3:
Differentiate the FOC for $e_i(p,1)$ to get

$$\underbrace{\omega_i\kappa e_i(p,1)^{\kappa-1}}_{>0}\frac{\partial e_i(p,1)}{\partial p}=\delta\frac{\partial}{\partial p}\left[f(\theta(p))\left[\mathbb{E}_pW_i(p')-\mathbb{E}_pT_i(p')\right]\right].$$

We need to find sufficient conditions so that the right-hand side of this equation is positive. We find, noting that p denotes *log* productivity,

$$\begin{aligned}\frac{\partial}{\partial p}\left[f(\theta(p))\left[\mathbb{E}_pW_i(p')-\mathbb{E}_pT_i(p')\right]\right]&=\frac{\partial f}{\partial\theta}\frac{\partial\theta}{\partial p}\left[\mathbb{E}_pW_i(p')-\mathbb{E}_pT_i(p')\right]+f(\theta)\left(\frac{\partial\mathbb{E}_pW_i(p')}{\partial p}-\frac{\partial\mathbb{E}_pT_i(p')}{\partial p}\right)\\&=\int(W_i(p')-T_i(p'))\left[\frac{\partial f}{\partial\theta}\frac{\partial\theta}{\partial p}g(p'|p)+f(\theta)\frac{\partial g(p'|p)}{\partial p}\right]dp'\\&=\int\underbrace{(W_i(p')-T_i(p'))}_{>0}f(\theta)\Bigg[\underbrace{\frac{\partial f}{\partial\theta}\frac{\theta}{f(\theta)}}_{(1-\alpha)}\underbrace{\frac{\partial\theta}{\partial p}\frac{1}{\theta}}_{\varepsilon_{\theta,p}}\\&\qquad+\underbrace{\frac{\partial g(p'|p)}{\partial p}\frac{1}{g(p'|p)}}_{\varepsilon_{g,p}}\Bigg]g(p'|p)\,dp'.\end{aligned}$$

Hence, $(1-\alpha)\varepsilon_{\theta,p}+\varepsilon_{g,p}>0$ guarantees that the entire integral is positive, implying $\partial e_i(p,1)/\partial p>0$. The argument for $e_i(p,0)$ is analogous.

PROOF OF PROPOSITION 2.4:

First, observe that if $k_i(p)=1$ or $k_i(p)=0$ for all $p\in[\underline{p},\overline{p}]$, then person i follows a cutoff rule trivially since we can set the cutoff to $\overline{p}+\epsilon$ or $\underline{p}-\epsilon$ where $\epsilon>0$ and $\epsilon\to 0$, respectively.

For all cases where i changes the take-up decision in the interior of $[\underline{p},\overline{p}]$, if person i follows a cutoff rule in take-up, then $N_i(p_0)>T_i(p_0)-\psi$ implies $N_i(p_1)>T_i(p_1)-\psi$ for $p_1>p_0$. A sufficient condition for this is that $\frac{\partial N_i(p)}{\partial p}>\frac{\partial T_i(p)}{\partial p}$ for all p.

Differentiating (2.5) and (2.6) with respect to p, we find (using $f(p)=f(\theta(p))$ as a shorthand):

$$\begin{aligned}\frac{\partial N_i(p)}{\partial p}&=\delta\frac{\partial \mathbb{E}_pU_i(p')}{\partial p}+\delta e_i(p,0)\frac{\partial}{\partial p}\left[f(p)\left(\mathbb{E}_pW_i(p')-\mathbb{E}_pU_i(p')\right)\right]\\ \frac{\partial T_i(p)}{\partial p}&=\delta\frac{\partial \mathbb{E}_pT_i(p')}{\partial p}+\delta e_i(p,1)\frac{\partial}{\partial p}\left[f(p)\left(\mathbb{E}_pW_i(p')-\mathbb{E}_pT_i(p')\right)\right].\end{aligned}$$

By differentiating the two FOCs for search effort and imposing $\partial e_i(p,0)/\partial p>0$ and $\partial e_i(p,1)/\partial p>0$ we find

$$\frac{\partial}{\partial p}\left[f(p)\left(\mathbb{E}_pW_i(p')-\mathbb{E}_pU_i(p')\right)\right]>0$$

and

$$\frac{\partial}{\partial p}\left[f(p)\left(\mathbb{E}_pW_i(p')-\mathbb{E}_pT_i(p')\right)\right]>0.$$

Hence, denoting by $g(p'|p)$ and $G(p'|p)$ the conditional pdf and cdf of p' given p, respectively, and using $e_i(p,0)>e_i(p,1)$ by Proposition 2,

$$\begin{aligned}\frac{\partial N_i(p)}{\partial p}-\frac{\partial T_i(p)}{\partial p}&>\delta\left(\frac{\partial \mathbb{E}_pU_i(p')}{\partial p}-\frac{\partial \mathbb{E}_pT_i(p')}{\partial p}\right)+\delta e_i(p,1)\frac{\partial}{\partial p}\left[f(p)\left(\mathbb{E}_pT_i(p')-\mathbb{E}_pU_i(p')\right)\right]\\ &=\delta\left(\frac{\partial \mathbb{E}_pU_i(p')}{\partial p}-\frac{\partial \mathbb{E}_pT_i(p')}{\partial p}\right)+\delta e_i(p,1)\Bigg[\underbrace{\frac{\partial f(p)}{\partial p}\left(\mathbb{E}_pT_i(p')-\mathbb{E}_pU_i(p')\right)}_{>0\text{ by Lemma 1}}\\ &\qquad+f(p)\left(\frac{\partial \mathbb{E}_pT_i(p')}{\partial p}-\frac{\partial \mathbb{E}_pU_i(p')}{\partial p}\right)\Bigg]\\ &>\delta(1-e_i(p,1)f(p))\left(\frac{\partial \mathbb{E}_pU_i(p')}{\partial p}-\frac{\partial \mathbb{E}_pT_i(p')}{\partial p}\right)\end{aligned}$$

$$= \delta(1 - e_i(p,1)f(p)) \int \underbrace{(U_i(p') - T_i(p'))}_{=\max\{-\psi, N_i(p') - T_i(p')\}} \frac{\partial g(p'|p)}{\partial p} \, dp'$$

$$= \delta(1 - e_i(p,1)f(p)) \int \frac{\partial \max\{-\psi, N_i(p') - T_i(p')\}}{\partial p'} \left(-\frac{\partial G(p'|p)}{\partial p} \right) dp',$$

where the last step follows from integration by parts. Noting that

$$G(p'|p) = \mathbb{P}(\varepsilon' \leq p' - \rho p | p)$$

and hence

$$\frac{\partial G(p'|p)}{\partial p} = -\rho g(p'|p),$$

we find, for all p,

$$\frac{\partial N_i(p)}{\partial p} - \frac{\partial T_i(p)}{\partial p} > \delta(1 - e_i(p,1)f(p))\rho \int \underbrace{\frac{\partial \max\{-\psi, N_i(p') - T_i(p')\}}{\partial p'}}_{\in\left\{0, \frac{\partial N_i(p')}{\partial p'} - \frac{\partial T_i(p')}{\partial p'}\right\}} g(p'|p) \, dp'$$

$$> \underbrace{\delta(1 - e_i(p,1)f(p))\rho}_{\in(0,1)} \underbrace{\int \min\left\{0, \frac{\partial N_i(p')}{\partial p'} - \frac{\partial T_i(p')}{\partial p'}\right\} g(p'|p) \, dp'}_{\leq 0}$$

$$> \int \min\left\{0, \frac{\partial N_i(p')}{\partial p'} - \frac{\partial T_i(p')}{\partial p'}\right\} g(p'|p) \, dp'.$$

Define $\phi(p) \equiv \frac{\partial N_i(p)}{\partial p} - \frac{\partial T_i(p)}{\partial p}$. We want to prove that $\phi(p) > 0$ for all p. To the contrary, assume that $\exists p : \phi(p) \leq 0$. Define $\underline{\phi} \equiv \min_p \phi(p)$. We have $\underline{\phi} \leq 0$ by assumption. The previous inequality holds for all p, among them $\underline{p}$ so that $\phi(\underline{p}) = \underline{\phi}$. Picking $p = \underline{p}$, we find

$$\underline{\phi} > \int \min\{0, \phi(p')\} g(p'|p) \, dp' \geq \int \min\left\{0, \underline{\phi}\right\} g(p'|p) \, dp' = \min\left\{0, \underline{\phi}\right\} = \underline{\phi},$$

which is a contradiction. Hence $\frac{\partial N_i(p)}{\partial p} > \frac{\partial T_i(p)}{\partial p}$ for all p, which establishes the result.

PROOF OF PROPOSITION 2.5:

If the government runs a balanced budget every period, we have

$$(1 - u_t)\tau_t = u_{1t} z \ \forall t,$$

where τ_t denotes the lump-sum tax on workers. Differentiating with respect to z and rewriting, we find

$$\frac{1-u_t}{u_{1t}}\frac{\partial \tau_t}{\partial z} = 1 + \frac{\partial u_{1t}}{\partial z}\frac{z}{u_{1t}} + \frac{\partial u_t}{\partial z}\frac{z}{u_t}\frac{u_t}{1-u_t}.$$

Moreover, given a small increase in z in period t_0, we only need to look at first-order effects on aggregate welfare due to the envelope theorem. In particular, we only need to consider the impact on consumption when employed and unemployed, but we can ignore the impact on the probability of being registered, u_{1t}, and of being employed, $1-u_t$, since individuals choose search effort optimally. At the optimum we hence have

$$\sum_{t=t_0}^{\infty} u_{1t}\delta^{t-t_0}v'(c_u) - (1-u_t)\delta^{t-t_0}v'(c_e)\frac{\partial \tau_t}{\partial z} = 0$$
$$\Leftrightarrow \sum_{t=t_0}^{\infty} \delta^{t-t_0}u_{1t}v'(c_e)\left(\frac{v'(c_u)}{v'(c_e)} - \frac{1-u_t}{u_{1t}}\frac{\partial \tau_t}{\partial z}\right) = 0.$$

Plugging in from above, we find

$$\sum_{t=t_0}^{\infty} \delta^{t-t_0}u_{1t}\left(\frac{v'(c_u)-v'(c_e)}{v'(c_e)} - \frac{\partial u_{1t}}{\partial z}\frac{z}{u_{1t}} - \frac{\partial u_t}{\partial z}\frac{z}{u_t}\frac{u_t}{1-u_t}\right) = 0,$$

which directly implies the result.

Moreover, if third-order terms of $v(c)$ are small, a Taylor approximation implies

$$v'(c_u) \approx v'(c_e) - v''(c_e)(c_e - c_u)$$
$$\Leftrightarrow \frac{v'(c_u)-v'(c_e)}{v'(c_e)} \approx \underbrace{-\frac{v''(c_e)}{v'(c_e)}c_e}_{\equiv\gamma}\frac{c_e-c_u}{c_e}.$$

PROOF OF PROPOSITION 2.6:

At the optimum, the derivatives of $C_t(V_t^l, V_t^h)$ with respect to $z(t)$ and $z(t+1)$ are zero:

$$-1-\delta^2(1-e_l(t))(1-e_l(t+1))\left[\frac{\partial C_{t+2}(\cdot)}{\partial V_{t+2}^l}\frac{\partial V_{t+2}^l}{\partial z(t)} + \frac{\partial C_{t+2}(\cdot)}{\partial V_{t+2}^h}\frac{\partial V_{t+2}^h}{\partial z(t)}\right]$$
$$+\delta C_{t+1}(\cdot)\frac{\partial e_l(t)}{\partial z(t)} + \delta^2(1-e_l(t))C_{t+2}(\cdot)\frac{\partial e_l(t+1)}{\partial z(t)} = 0$$

$$- \delta(1-e_l(t)) - \delta^2(1-e_l(t))(1-e_l(t+1)) \left[\frac{\partial C_{t+2}(\cdot)}{\partial V^l_{t+2}} \frac{\partial V^l_{t+2}}{\partial z(t+1)} + \frac{\partial C_{t+2}(\cdot)}{\partial V^h_{t+2}} \frac{\partial V^h_{t+2}}{\partial z(t+1)} \right]$$
$$+ \delta C_{t+1}(\cdot) \frac{\partial e_l(t)}{\partial z(t+1)} + \delta^2(1-e_l(t)) C_{t+2}(\cdot) \frac{\partial e_l(t+1)}{\partial z(t+1)} = 0$$

Using implicit differentiation in the constraints, we find:

$$\begin{aligned}
\frac{\partial V^l_{t+2}}{\partial z(t)} &= -\frac{u'(\ell+z(t))}{\delta^2(1-e_l(t))(1-e_l(t+1))} \\
\frac{\partial V^h_{t+2}}{\partial z(t)} &= -\frac{u'(\ell+z(t))}{\delta^2(1-e_h(t))(1-e_h(t+1))} \\
\frac{\partial V^l_{t+2}}{\partial z(t+1)} &= -\frac{u'(\ell+z(t))}{\delta(1-e_l(t+1))} \\
\frac{\partial V^h_{t+2}}{\partial z(t+1)} &= -\frac{u'(\ell+z(t))}{\delta(1-e_h(t+1))} \\
\frac{\partial e_l(t)}{\partial z(t)} &= -\frac{\delta}{\omega_l \kappa} e_l(t)^{1-\kappa} \delta(1-e_l(t+1)) \frac{\partial V^l_{t+2}}{\partial z(t)} = \frac{e_l(t)^{1-\kappa}}{1-e_l(t)} \frac{u'(\ell+z(t))}{\omega_l \kappa} \\
\frac{\partial e_l(t+1)}{\partial z(t)} &= -\frac{\delta}{\omega_l \kappa} e_l(t+1)^{1-\kappa} \frac{\partial V^l_{t+2}}{\partial z(t)} = \frac{e_l(t)^{1-\kappa}}{\delta(1-e_l(t))(1-e_l(t+1)} \frac{u'(\ell+z(t))}{\omega_l \kappa} \\
\frac{\partial e_l(t)}{\partial z(t+1)} &= -\frac{\delta}{\omega_l \kappa} \left[u'(\ell+z(t+1)) + \delta(1-e_l(t+1)) \frac{\partial V^l_{t+2}}{\partial z(t+1)} \right] = 0 \\
\frac{\partial e_l(t+1)}{\partial z(t+1)} &= -\frac{\delta}{\omega_l \kappa} e_l(t+1)^{1-\kappa} \frac{\partial V^l_{t+2}}{\partial z(t+1)} = \frac{e_l(t+1)^{1-\kappa}}{(1-e_l(t+1)} \frac{u'(\ell+z(t+1))}{\omega_l \kappa}
\end{aligned}$$

Plugging in above and simplifying, we find

$$\begin{aligned}
\frac{1}{u'(\ell+z(t))} =& \frac{\partial C_{t+2}(\cdot)}{\partial V^l_{t+2}} + \frac{(1-e_l(t))(1-e_l(t+1))}{(1-e_h(t))(1-e_h(t+1))} \frac{\partial C_{t+2}(\cdot)}{\partial V^h_{t+2}} + \frac{\delta}{\omega_l \kappa} C_{t+2}(\cdot) \frac{e_l(t+1)^{1-\kappa}}{1-e_l(t+1)} \\
&+ \frac{\delta}{\omega_l \kappa} C_{t+1}(\cdot) \frac{e_l(t)^{1-\kappa}}{1-e_l(t)} \\
\frac{1}{u'(\ell+z(t+1))} =& \frac{\partial C_{t+2}(\cdot)}{\partial V^l_{t+2}} + \frac{1-e_l(t+1)}{1-e_h(t+1)} \frac{\partial C_{t+2}(\cdot)}{\partial V^h_{t+2}} + \frac{\delta}{\omega_l \kappa} C_{t+2}(\cdot) \frac{e_l(t+1)^{1-\kappa}}{1-e_l(t+1)}.
\end{aligned}$$

To find the envelope conditions, we need to ask how the current cost $C_t(V^l_t, V^h_t)$ is affected by changes in V^l_t and V^h_t starting from the optimum. The principal can change V^l_t and V^h_t by changing $z(t)$ and $z(t+1)$. Using the envelope theorem, a marginal change in $z(t)$ satisfies

$$1 = \frac{\partial C_t(\cdot)}{\partial V^l_t} u'(\ell+z(t)) + \frac{\partial C_t(\cdot)}{\partial V^h_t} u'(\ell+z(t)).$$

For a marginal change in $z(t+1)$, we have to take into account that $e_l(t)$ reacts as we keep V^l_{t+2} constant:

$$\delta(1-e_l(t)) + \delta C_{t+1}(\cdot) \frac{\delta}{\omega_l \kappa} e_l(t)^{1-\kappa} u'(\ell+z(t+1)) = \delta(1-e_l(t)) \frac{\partial C_t(\cdot)}{\partial V^l_t} u'(\ell+z(t+1)) + \delta(1-e_h(t)) \frac{\partial C_t(\cdot)}{\partial V^h_t} u'(\ell+z(t+1))$$

Solving this system of equations for $\frac{\partial C_t(\cdot)}{\partial V_t^l}$ and $\frac{\partial C_t(\cdot)}{\partial V_t^h}$, we find

$$\begin{aligned}
\frac{\partial C_t(\cdot)}{\partial V_t^l} &= \frac{1-e_l(t)}{e_h(t)-e_l(t)}\left(\frac{1}{u'(\ell+z(t+1))}+\frac{\delta}{\omega_l\kappa}C_{t+1}(\cdot)\frac{e_l(t)^{1-\kappa}}{1-e_l(t)}\right)-\frac{1-e_h(t)}{e_h(t)-e_l(t)}\frac{1}{u'(\ell+z(t))}\\
\frac{\partial C_t(\cdot)}{\partial V_t^h} &= -\frac{1-e_l(t)}{e_h(t)-e_l(t)}\left(\frac{1}{u'(\ell+z(t+1))}+\frac{\delta}{\omega_l\kappa}C_{t+1}(\cdot)\frac{e_l(t)^{1-\kappa}}{1-e_l(t)}-\frac{1}{u'(\ell+z(t))}\right).
\end{aligned}$$

PROOF OF LEMMA 4:

Given that the high types can be excluded, there is only one state variable and it suffices to solve for the optimal benefits one period at a time. The recursive problem now reads

$$C_t(V_t^l) = \min_{z(t),V_{t+1}^l} \left\{z(t)+\delta(1-e_l(t))C_{t+1}(V_{t+1}^l)\right\}$$

subject to

$$\begin{aligned}
u(\ell+z(t)) - \frac{\omega_l}{1+\kappa}e_l(t)^{1+\kappa} + \delta(1-e_l(t))V_{t+1}^l &= V_t^l\\
\omega_l e_l(t)^\kappa &= -\delta V_{t+1}^l.
\end{aligned}$$

At the optimum, the derivative with respect to $z(t)$ has to be zero, hence

$$-1-\delta(1-e_l(t))\frac{\partial C_{t+1}(\cdot)}{\partial V_{t+1}^l}\frac{\partial V_{t+1}^l}{\partial z(t)}+\delta C_{t+1}(\cdot)\frac{\partial e_l(t)}{\partial z(t)}=0.$$

Implicit differentiation in the constraints implies

$$\begin{aligned}
\frac{\partial V_{t+1}^l}{\partial z(t)} &= -\frac{u'(\ell+z(t))}{\delta(1-e_l(t))}\\
\frac{\partial e_l(t)}{\partial z(t)} &= \frac{u'(\ell+z(t))}{\omega_l\kappa}\frac{e_l(t)^{1-\kappa}}{1-e_l(t)}.
\end{aligned}$$

Moreover, the envelope theorem implies

$$\frac{\partial C_t(\cdot)}{\partial V_t^l} = \frac{1}{u'(\ell+z(t))}.$$

Plugging in above and simplifying yields the desired result.

3 Quasi-experimental Evidence on Take-up and the Value of Unemployment Insurance

Joint with François Fontaine

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3.1 Introduction

Unemployment insurance (hereafter UI) helps individuals to smooth consumption when they are unemployed. From this perspective, unemployment insurance take-up is an intriguing phenomenon. In most of the existing studies, it lies between 25% and 75% (see Table 3.1), suggesting that claiming costs are high in comparison with the value of unemployment insurance. In this paper, we try to quantify the net value of UI by finding a monetary equivalent of the intertemporal utility of claiming and receiving UI relative to not doing so. For this purpose, we study a large Austrian administrative database where discontinuities in eligibility for severance payments (SP) and extended unemployment benefits (EB) create variation in take-up rates and in the exit rate from unemployment. We first provide a simple search model where workers face a cost of claiming for unemployment benefits and can partially smooth consumption using savings. In the spirit of Card et al. (2007), we show that reduced-form estimates of the impact of SP and EB on take-up rates and exit rates can be used to compute bounds on a money metric for the net value of UI.

Following seminal work by Moffitt (1983) on welfare benefits, previous studies on UI take-up primarily focused on empirical investigations of its determinants. These are sur-

[1] The British Department for Work and Pensions (DWP) is one of the few government agencies that regularly publish estimates of take-up rates.

Country	Source	Estimated take-up	Time period
Canada	Storer and van Audenrode (1995)	77%	1981 – 1986
France	Blasco and Fontaine (2012)	27% - 45%	2001 – 2002
United Kingdom	DWP[1] (2012)	49% - 84%	1997 – 2010
United States	Anderson and Meyer (1997)	24% - 50%	1979 – 1982
	Blank and Card (1991)	68% - 75%	1977 – 1987
	McCall (1995)	65%	1982 – 1991

Table 3.1: Overview of estimated take-up in existing studies

veyed in Currie (2004) and Hernanz et al. (2004). Notable examples are Blank and Card (1991), McCall (1995) and Anderson and Meyer (1997), all finding that generosity of UI is a significant determinant of take-up[2] which is consistent with agents comparing costs and benefits of UI take-up. Claiming costs *per se* have been the focus of a number of studies (e.g. Bhargava and Manoli (2015), Budd and McCall (1997), Ebenstein and Stange (2010), Kopczuk and Pop-Eleches (2007)). While existing evidence is inconclusive as to their exact composition (physical costs, psychological costs or administrative barriers to filing; see descriptive evidence in Vroman (2009)), they point to a significant role for take-up costs. Finally, low take-up rates could be understood as the result of errors in individuals' assessment of their eligibility. Following this idea, a recent paper Hertel-Fernandez and Wenger (2013) describes an experiment where randomly selected unemployed were provided accurate information about UI eligibility requirements. Contrary to expectation, treated individuals actually displayed lower participation. The authors interpret the finding as a consequence of uncertainty about actual take-up costs. In comparison with existing studies, we try to quantify directly the two sides of the take-up choice, namely the claiming costs and the welfare gains from UI.

Only recently have there been attempts to come up with structural models to explain the take-up process in more detail. One of them is Blasco and Fontaine (2012), who incorporate a take-up decision in a detailed partial equilibrium job search model and estimate it on administrative data. They show that the take-up decision, job search behavior and expectations are deeply interrelated and that the elasticity of the exit rate to unemployment benefits depends on the elasticity of the take-up rate. In this paper, we allow the take-up rate to depend on job search efficiency and the search behavior to be affected by claiming, while focusing on the quantification of the value of UI.

Recent studies by Auray et al. (2013), Chodorow-Reich and Karabarbounis (2014)

[2]Burtless (1983) is probably among the first to document the stylized fact and to explore possible explanations.

and Kettemann (2016) incorporate UI take-up in an equilibrium model. The first is only relevant for a system where firms are experience rated and pay higher payroll taxes if more of their previous employees collected benefits. In this case, since firms prefer workers not taking up UI, these will enjoy higher job arrival rates and workers will select endogenously into registered and non-registered unemployment. Chodorow-Reich and Karabarbounis (2014) introduce a take-up decision into a DSGE model with matching frictions and a representative household in order to calculate the cyclicality of the opportunity cost of employment. Kettemann (2016) introduces a take-up decision in a search and matching model with linear preferences, hence abstracting from savings, and endogenous search effort. He shows that take-up and search effort interact to amplify fluctuations of labor market aggregates along the business cycle. Moreover, he demonstrates that endogenous take-up can have important consequences for the optimal time structure of unemployment benefits, potentially making the schedule upward sloping. In all cases, the strategy and purpose is different from ours. Our main objective is to identify the distribution of the net value of UI using data on take-up behavior and exit rates from unemployment. Moreover, by relying on estimates from a regression discontinuity design, we are, to our knowledge, the first to come up with quasi-experimental evidence on UI take-up.

The data, together with some information on the institutional background, are presented in section 3.2. We then develop a simple search model with UI take up in section 4.6, from which we build our empirical strategy in section 3.4. Section 4.8 is devoted to the empirical findings, while section 4.10 concludes.

3.2 Institutional Background and Data

In this section we briefly describe the institutional background motivating our empirical strategy. We are going to use two discontinuities in the data: the first is related to eligibility for severance payments, the second to eligibility for extended UI benefits.

On the one hand, firms are required to make a lump-sum transfer at the time of the layoff, whose size depends on a step function of the worker's tenure in the firm[3]. In particular, jobs below three years of tenure at the time of the separation are not eligible for mandatory severance pay. After three years, firms have to make a transfer of at least two months of salary.

In addition, workers having lost their job can collect benefits if they have acquired a sufficient work history (those who quit face a waiting period of 28 days). Workers who have worked at least twelve months out of the two years preceding job loss are able to

[3]For all jobs starting as of January 1, 2003, mandatory severance pay was abolished and succeeded by a system of occupational pensions.

claim. The maximum benefit duration, in turn, depends on the months worked in the five years preceding job loss. If a worker was employed for below 36 months, she is eligible for up to twenty weeks of benefits, while those having worked for more than 36 months are eligible for 30 weeks. Benefits replace approximately 55% of previous earnings up to a minimum and a maximum, though the maximum is attained by very few people. Importantly, unemployment insurance has to be claimed personally at the local office of the public employment service Austria (AMS).

As discussed by Card et al. (2007), this setting implies a "double-disconinuity" problem. For around 50% of all jobs in our baseline sample[4], the threshold of receiving severance pay coincides with the threshold of receiving extended benefits. Card et al. (2007) show that the effects of eligibility for severance pay and extended benefits can still be separated since labor market experience and job tenure are not perfectly correlated for all individuals.

We use data from the Austrian Social Security Database (ASSD). ASSD covers the universe of Austrian private sector workers (about 80% of the entire workforce), providing longitudinal information from 1972 onwards. The data have been collected in order to verify old-age pension claims and hence covers all information relevant for this aim. In particular, it reports individuals' complete earnings and employment history, as well as other labor market states, such as registered unemployment, sickness or maternal leave.

For our analysis, we focus on terminations from jobs that started between January 1, 1981 and December 31, 2002. For all jobs starting after January 1, 2003, the severance payment scheme was abolished in favor of an occupational pension scheme. In order to limit the interaction with special programs for older workers, we drop workers above 50 years of age at the time of their job loss and/or retiring within the same calendar year. We also exclude workers below 25 (as their jobs are often fixed-term apprenticeships), terminations from jobs in the construction industry (as they are subject to a different severance regulation). Following Card et al. (2007), we exclude terminations from hospitals, schools, and other public sector service industries, as some of these jobs are fixed-term. Lastly, we exclude workers recalled to their previous employer, as they might not be searching for a job, and those that never return to a job.

Unfortunately, the ASSD does not record non-registered unemployment (non take-up) explicitly, but we have to infer this from a gap in the working history. We code such a nonemployment spell as registered if it overlaps with an unemployment insurance spell in the data, while we code it as non-registered if no such spell is observed. While the requirement that the workers in our sample return to the labor market at a later stage ensures some labor force attachment, we are not entirely able to distinguish between non-

[4]The number is 20% in Card et al. (2007), as they use a larger bandwidth and also include very young ($<$ 25 years) workers.

registered unemployment and non-participation. Due to unobserved non-participation, there is a long tail of extremely long nonemployment durations in the data. To limit their influence on the results, we follow Card et al. (2007) and censor spells at 2 years.

Moreover, while many spells apart from employment and registered unemployment are observed in the data (such as sickness, retirement, maternal leave, etc.), there are certain labor market states that are not recorded in the data, such as self-employment or a stay abroad. This might lead to some of these states being erroneously coded as non-registered unemployment. As will become apparent later on, however, this limitation will not have a crucial effect on our results if we can assume that all relevant unobserved states trend smoothly around the two discontinuities.

In Table 3.2, we list some summary statistics for all job terminations and the estimation sample, using a bandwidth of 12 months around the cutoffs for severance pay and extended benefits. The sample selection criteria we have to apply result in some obvious differences between the entire population and the estimation sample. By construction, we focus on workers with relatively high tenure at their previous employer, while on average jobs have a quite low duration. Workers in the sample are also more likely to be female, slightly older, more experienced, and facing a slightly longer unemployment spell. The take-up rate is also considerably higher, which is also due to the fact that many workers in the entire population are not eligible for unemployment insurance. Then again, it is reassuring that the sample at hand does not seem to differ much from the overall population in terms of the pre-displacement wage.

	All Job Terminations	Estimation Sample
Female (%)	48.65	66.18
Age	31.29	34.43
Experience (years)	5.98	6.71
Austrian citizen (%)	83.00	78.19
Tenure at previous job (years)	1.89	2.78
Nonemployment duration	253.54	321.08
Take-up rate (%)	36.80	66.05
Blue-collar worker (%)	58.85	64.79
Monthly wage (year 2000 Euros)	1458.06	1457.68
Observations	7753856	83451

Table 3.2: Summary statistics for all job losers and the estimation sample

3.3 Theoretical Framework

We provide a model where workers are, among other things, heterogeneous in terms of wealth when entering unemployment. When becoming unemployed, they face a cost of claiming for unemployment benefits and evaluate the gain from unemployment insurance by taking into account their ability to smooth consumption using savings. For some of them, claiming is too costly and they will thus only rely on their accumulated wealth in doing so, which will, in turn, affect their search behavior. Besides, since eligibility for severance payments is similar to a wealth shock, it will likely affect both search behavior and willingness to claim. The same applies for eligibility for extended benefits which renders unemployment insurance more attractive. In the following model, we will give a formal derivation of (i) how exit rates react to eligibility for extended benefits, and (ii) how the take-up rate responds to eligibility for severance pay and extended benefits.

3.3.1 The Model

Time is discrete and the first period is 0. When a worker becomes unemployed, she decides whether to claim unemployment benefits, which is costly. The claiming cost is denoted by ϕ and it is assumed to be distributed in the population of unemployed workers according to a distribution with cdf F and pdf f. If unemployment benefits have been claimed when entering unemployment, income during unemployment is b_t^I, if not, it is $b_t^{\bar{I}}$. We also assume that for each state, there might be other costs/benefits, denoted by δ_t^j, $j \in \{I, \bar{I}\}$, that represent social or administrative constraints, stigma or psychological costs and benefits. This means that, while there is a fixed cost of claiming, individuals may also have to bear costs for every period they collect benefits. In the same way, there can be benefits beyond benefit collection. We introduce these costs and benefits in terms of a monetary equivalent. Adding a second argument to the utility function, in addition to consumption, wouldn't affect our results[5].

For a worker with A_0 asset holdings, $U_0^I(A_0)$ denotes the intertemporal value of the claimants and $U_0^{\bar{I}}(A_0)$ the intertemporal value of non-claimants, both in period 0. The worker collects unemployment benefits if

$$U_0^I(A_0) - U_0^{\bar{I}}(A_0) \geq \phi.$$

Then, in each period, the timing is the following. First, workers make their consumption choices. Workers can save or dissave but, due to borrowing constraints, there is a lower limit on A (this is not explicit below to simplify the presentation). Then they choose their search intensity s_t^j ($j = I$ if collecting benefits, $j = \bar{I}$ if not), equal to the probability of obtaining an offer, at a cost $\psi(s_t^I)$. If they get an offer, they become imme-

[5]The main reason is that we don't have to go beyond deriving the behavioral response to a change in wealth and to longer benefit duration.

diately employed with an intertemporal value $V_{t+1}^{j}(A_{t+1})$, if not they stay unemployed. The intertemporal values at time t in both states satisfy, with β the discount rate and r the interest rate,

$$U_t^j(A_t) = u\Big(A_t - (1+r)^{-1}A_{t+1} + b_t^j - \delta_t^j\Big) - \psi(s_t^j) \\ + \beta\Big(s_t^j V_{t+1}^j(A_{t+1}) + (1-s_t^j)U_{t+1}^j(A_{t+1})\Big),$$

where $j \in \{0,1\}$. The value of employment in t is denoted by $V_t^j(A_t)$ and depends on the level of assets and possibly on the state of origin (claimants or non-claimants).

3.3.2 Job Search and Take-up Choices

In the following, we characterize optimal behavior, focusing on the effects we will use later on, namely the effect of assets and extended benefits on take-up and the effect of extended benefits on the exit rate. The first-order condition for search intensity reads

$$\psi'(s_{jt}) = \beta\left(V_{t+1}^j(A_{t+1}) - U_{t+1}^j(A_{t+1})\right), \tag{3.1}$$

with $j \in \{I, \bar{I}\}$. The effect of a future benefit increase in period $t+s$ on exits in period t, using (3.1) and the envelope condition, follows as

$$\frac{ds_{It}}{db_{t+s}} = -\frac{1}{\psi''(s_{It})}\beta^s p_{t+s|t+1} u'(c_{It+s}), \tag{3.2}$$

where $p_{t+s|t+1} \equiv \prod_{i=t+1}^{t+s-1}(1-s_{Ii})$ for $s > 1$, and 1 otherwise, denotes the probability of being unemployed in period $t+s$ if unemployed after $t+1$ periods. Because they raise the value of unemployment, future benefits decrease current search effort. The particular ordering of the effects on the exit rates from s_{I0} to s_{IT-1} depends on the changes in $\psi''(s_{It})$ and c_{It+s}[6] and is theoretically ambiguous.

Another way of expressing it, which will be more convenient especially when dealing with extensions of unemployment insurance over many periods, is to express it in terms of the marginal effect on *intertemporal* utility in period T, where T denotes the first period where the extension takes place. Denote by b^e the benefit level during the extension period and E the number of periods of this extension. The total effect on exits in period t is then given by

$$\frac{ds_{It}}{db^e} = -\frac{1}{\psi''(s_{It})}\beta^{T-t} p_{T|t+1}\frac{\partial U_T^I}{\partial b^e}. \tag{3.3}$$

[6] If net benefits, $b_t^I - \delta_t^I$, are decreasing over time, consumption is decreasing as well.

Considering, as we will later on, the effect of becoming eligible for extended benefits on search effort in the last period prior to the extension, $T-1$, one gets

$$\frac{ds_{IT-1}}{db^e} = \frac{ds_{IT-1}}{db_T} + ... + \frac{ds_{IT-1}}{db_{T+E}} \tag{3.4}$$

where $b_T = ... = b_{T+E} = b^e$.

We now look at the incentive to claim for unemployment benefits. Savings help workers to smooth consumption in unemployment and decrease the incentive to exit unemployment quickly. Notice that while the agent knows the claiming cost, we don't observe this cost in the data. From the econometrician's point of view, take-up can thus be considered probabilistic. The worker collects unemployment benefits if

$$U_0^I(A_0) - U_0^{\bar{I}}(A_0) \geq \phi,$$

which happens with probability $F\left(U_0^I(A_0) - U_0^{\bar{I}}(A_0)\right)$. The effects of assets and extended benefits on this take-up probability, denoted by ℓ, are:

$$\frac{d\ell}{dA_0} = f\left(U_0^I - U_0^{\bar{I}}\right)\left(u'(c_{I0}) - u'(c_{\bar{I}0})\right) \tag{3.5}$$

$$\frac{d\ell}{db^e} = f\left(U_0^I - U_0^{\bar{I}}\right)\beta^{T-1}p_{T|1}\frac{\partial U_T^I}{\partial b^e} \tag{3.6}$$

Eligibility for extended benefits increases unambiguously the probability to claim by raising the value of unemployment insurance. In the same way, as long as $c_{I0} > c_{\bar{I}0}$, a one-dollar increase in wealth will affect utility of the non-claimants by more than the utility of the benefit recipient due to decreasing marginal utility of consumption. Thus, the utility difference and the incentive to claim decrease. Both reactions are scaled by the density of marginal workers.

3.4 Empirical Strategy

Our empirical strategy borrows from Card et al. (2007) and Chetty (2008). The idea is to identify the value of UI using reduced-form estimates of the impacts of extended benefits (EB) and severance payments (SP) on the exit rates and on the take-up rate. For the sake of presentation, we explain our strategy in reverse order. We start by defining our money metric, assuming that we have estimates for the individual take-up probabilities, the effects of EB and SP, and estimates of the claiming cost distribution and the search cost function. Second, we show how reduced-form estimates can be used to get parameters for the two latter objects. Finally, we present the RDD which captures the behavioral response to EB and SP.

The general idea of our empirical strategy is the following. We don't observe individual claiming costs, ϕ. However, the estimated take-up probabilities are informative about the intertemporal utility difference, $U_0^I - U_0^{\bar{I}}$. The higher the probability, the bigger this difference. Moreover, the fact that workers react differently to eligibility for extended benefits or severance pay is indicative about how a money transfer impacts their welfare. Under parametric assumptions for F and ψ, this enables us to create a money metric for the value of UI.

3.4.1 The Value of Unemployment Insurance

We are looking for the asset transfer ΔA such that a non-claimant is indifferent between claiming and not claiming:

$$U_0^I(A_0) - \phi = U_0^{\bar{I}}(A_0 + \Delta A)$$

By definition, we have $\Delta A > 0$ for claimants, as they would have to be compensated for not claiming. This transfer compensates for the benefits they forgo but is reduced by the fact that they don't have to face the claiming costs. On the contrary, $\Delta A < 0$ for non-claimants. These individuals face high claiming costs relative to their value of unemployment benefits: They have enough assets or expect a quick exit from unemployment. They are thus willing to give up assets for not claiming.

A first-order Taylor approximation implies

$$\begin{aligned}\Delta A &\approx \left(U_0^I(A_0) - U_0^{\bar{I}}(A_0) - \phi\right)\left(\frac{dU_0^{\bar{I}}(A_0)}{dA_0}\right)^{-1} \\ &= \frac{U_0^I(A_0) - U_0^{\bar{I}}(A_0) - \phi}{u'(c_{\bar{I}0})},\end{aligned} \tag{3.7}$$

where the second step follows from the envelope theorem. Effectively, our approximation yields the difference in intertemporal utility, normalized by the utility value of one additional euro of consumption for the non-claimants. Note that, due to the concavity of the value function, a first-order compared to a second-order approximation will likely result in a downward biased ΔA (in absolute terms). If anything our measure underestimates the value of unemployment insurance among the claimants.

In the following, we will connect (3.7) to objects for which we have estimates: the take-up probability, the effect of assets and extended benefits on take-up, and the effect of extended benefits on the exit rate from unemployment. We need to determine the value of three elements: the intertemporal utility difference $U_{i0}^I - U_{i0}^{\bar{I}}$, the take-up cost ϕ and the marginal utility $u'(c_{\bar{I}0})$. Denote by p_i the take-up probability of individual i. First, observe that $U_{i0}^I - U_{i0}^{\bar{I}} = F^{-1}(p_i)$. Workers that have a high probability to claim are those for which the intertemporal utility difference is the biggest. Under parametric assumption for F and if we manage to get estimates of F's parameters, we can pin down this utility difference.

The fixed cost, ϕ_i, on the other hand, cannot be exactly identified. However, if we have an estimate of the probability of claiming, and since we observe the take-up decision, we can compute the expected value of ϕ_i among claimants and non-claimants,

$$\bar{\phi}_{i1} = \int_0^{F^{-1}(p_i)} \frac{x}{p_i}\, dF(x), \text{ and} \tag{3.8}$$

$$\bar{\phi}_{i0} = \int_{F^{-1}(p_i)}^{\phi^{sup}} \frac{x}{1-p_i}\, dF(x), \tag{3.9}$$

respectively. Note that this directly implies $U_0^I(A_0) - U_0^{\bar{I}}(A_0) - \bar{\phi}_0 < 0 \leq U_0^I(A_0) - U_0^{\bar{I}}(A_0) - \bar{\phi}_1$. Intuitively, a worker who claims despite having a low predicted take-up propensity is expected to have a low claiming cost (and vice versa).

$u'(c_{\bar{I}0})$, in turn, is impossible to pin down given our estimates. However, we can bound it. One insight we can use here is that a higher marginal value of consumption in the case where the individual does not collect benefits will translate into a stronger reaction of the take-up probability to a wealth shock. Remember that, in the data, eligibility for severance pay is equivalent to a wealth shock when entering unemployment. For a lower bound, observe that

$$u'(c_{\bar{I}0}) > u'(c_{\bar{I}0}) - u'(c_{I0}),$$

which can be connected to the marginal effect of assets on the claiming probability. Indeed, (3.5) directly implies

$$u'(c_{\bar{I}0}) - u'(c_{I0}) = -\frac{d\ell}{dA_0} \frac{1}{f\left(F^{-1}(p_i)\right)}$$

and thus $u'(c_{\bar{I}0}) - u'(c_{I0})$ is identified by the effect of assets on take-up. If one worker is more reactive than another to a wealth shock, it means that the utility value of one euro is higher for her than for the other. For the same intertemporal utility difference $U_0^I(A_0) - U_0^{\bar{I}}(A_0) - \phi$ this implies a lower *monetary* equivalent for the more responsive worker because her marginal value of consumption is higher.

For an upper bound, we use that

$$u'(c_{\bar{I}0}) = u'(c_{\bar{I}0}) - u'(c_{I0}) + u'(c_{I0}) \leq u'(c_{\bar{I}0}) - u'(c_{I0}) + u'(c_{IT}),$$

where the second equality holds as long as $c_{IT} \leq c_{I0}$[7] by the concavity of the utility function. We have already shown that $u'(c_{\bar{I}0}) - u'(c_{I0})$ is identified if we know the take-up response to a change in wealth. $u'(c_{IT})$, in turn, can be bounded using the effect of extended benefits on exits the period before the extension takes place, ds_{iIT-1}/db^e. Again, more responsive workers are those for whom one euro has a higher value in terms of utility. Assume that the UI extension takes place in period T and lasts until period $T+E$. The total marginal effect of increasing the benefit level in all E periods is given by

$$\frac{ds_{IT-1}}{db^e} = \frac{ds_{IT-1}}{db_T} + \ldots + \frac{ds_{IT-1}}{db_{T+E}}$$

Using (3.2), and again using that consumption is non-increasing over time, we find (note that $ds_{IT-1}/db_T < 0$)

$$\begin{aligned} \frac{ds_{IT-1}}{db^e} &= \frac{ds_{IT-1}}{db_T}\left[1 + \beta p_{T+1|T}\frac{u'(c_{IT+1})}{u'(c_{IT})} + \ldots + \beta^E p_{T+E|T}\frac{u'(c_{IT+E})}{u'(c_{IT})}\right] \\ &\leq \frac{ds_{IT-1}}{db_T}\underbrace{\left[1 + \beta p_{T+1|T} + \ldots + \beta^E p_{T+E|T}\right]}_{\equiv B}. \end{aligned}$$

Substituting for ds_{IT-1}/db_T using (3.2), we conclude

$$u'(c_{IT}) \leq -\frac{ds_{IT-1}}{db^e}\frac{\psi''(s_{IT-1})}{\beta B},$$

where B corrects for the fact that the extension affects multiple time periods.

Combining all previous steps, we conclude that the equivalent wealth transfer to the claimants satisfies

$$\frac{F^{-1}(p_i) - \bar{\phi}_1}{-\frac{d\ell}{dA_0}\frac{1}{f(F^{-1}(p_i))} - \frac{ds_{IT-1}}{db^e}\frac{\psi''(s_{IT-1})}{\beta B}} \leq \Delta A \leq \frac{F^{-1}(p_i) - \bar{\phi}_1}{-\frac{d\ell}{dA_0}\frac{1}{f(F^{-1}(p_i))}}, \tag{3.10}$$

while for the non-claimants

$$\frac{F^{-1}(p_i) - \bar{\phi}_0}{-\frac{d\ell}{dA_0}\frac{1}{f(F^{-1}(p_i))}} \leq \Delta A \leq \frac{F^{-1}(p_i) - \bar{\phi}_0}{-\frac{d\ell}{dA_0}\frac{1}{f(F^{-1}(p_i))} - \frac{ds_{IT-1}}{db^e}\frac{\psi''(s_{IT-1})}{\beta B}}. \tag{3.11}$$

[7]This is the case if $b_t^I - \delta_t^I$ is non-increasing over time.

3.4.2 Estimation of the Structural Parameters

In order to implement (3.10) and (3.11), we need estimates for the parameters of the claiming cost distribution and the search cost function. Start with p_i, the estimated probability of a given individual to be observed as receiving unemployment benefits. Assume we have such a value for each individual. Under parametric assumptions for $F(\phi)$, we can link this probability to the value of unemployment insurance:

$$U_{i0}^{I} - U_{i0}^{\bar{I}} = F^{-1}(p_i)$$

Together with (3.3) and (3.6) this directly implies

$$\begin{aligned} \frac{d\ell_i/db^e}{ds_{iIT-1}/db^e} \equiv M_i &= -f\left(U_{i0}^{I} - U_{i0}^{\bar{I}}\right)\beta^{T-2}p_{T|1}\psi_i''(s_{iIT-1}) \\ &= -f\left(F^{-1}(p_i)\right)\beta^{T-2}p_{T|1}\psi_i''(s_{iIT-1}). \end{aligned} \tag{3.12}$$

Equation (3.12) links the estimated probability of claiming and the behavioral response to eligibility for extended benefits to the parameters of the claiming cost distribution and the search cost function. We will specify these functions in subsection 3.5.3. However, we can already point out that these sets of parameters, denoted by θ and a, can be estimated by least squares, solving

$$\{\theta, a\} = \arg\min \sum_i \left(\ln(-M_i) - \ln\left(f\left(F^{-1}(p_i)\right)\beta^{T-2}p_{T|1}\psi_i''(s_{iIT-1})\right)\right)^2.$$

Intuitively, θ and a are identified by the variation of the relative response in take-up and search to extended benefits. The first depends on the take-up probability (driven by the F distribution, parameterized by θ) and the second hinges on the job-finding rate which is linked to the search cost function (parameterized by a). A high value of $-M_i$, indicating that the reaction of the take-up probability relative to the reaction of the job-finding rate to extended benefits is large, can be for two reasons: (i) A strong reaction in take-up if the density of the claiming cost distribution is high at the point determined by p_i $(f(F^{-1}(p_i)))$. (ii) A small reaction in unemployment exits if the curvature in the marginal costs $\psi_i''(s_{iIT-1})$ is high at s_{iIT-1}. Finally, notice that since the marginal utility of consumption enters in the same way in $d\ell_i/db^e$ as in ds_{iIT-1}/db^e, the moment M_i does not depend on the shape of the utility function, meaning that we can avoid having to make any parametric assumptions here.

3.4.3 Estimating the Effect of Extended Benefits and Severance Payments

Identification. The identification strategy is similar to Card et al. (2007). We use the quasi-experiment created by the sharp discontinuity in eligibility for severance pay and extended unemployment benefits in Austria. Eligibility for the former depends on job tenure, while eligibility for extended benefits depends on the number of months worked in the five preceding years. The effects of severance pay and extended benefits can thus be separated as job tenure in months, denoted by JT, and the number of months worked in the past, denoted by MW, are not perfectly correlated. On the one hand, there are workers who have lost a job having job tenure below three years, while having acquired around three years of work experience in the preceding five years. On the other hand, there are also workers who have around three years tenure while having surpassed three years work experience in the preceding five years. As in these cases only one of the two assignment variables jumps, the effects are identified.

Take-up probability. We use a probit model for take-up. We allow for cubic polynomials in the running variables and control for observed characteristics. We denote by S_i the eligibility dummy for severance pay and by E_i the eligibility for extended benefits. X_i is a vector of observable characteristics[8]. MW and JT are centered around the cutoffs, meaning that MW equals zero at 36 months worked and JT at 36 months of job tenure. The probability of collecting benefits, p_i, is assumed to satisfy

$$p_i = \Phi(y_i), \tag{3.13}$$

where

$$\begin{aligned} y_i = & \beta_S S_i + \beta_E E_i + \beta_1 JT_i + \beta_2 MW_i + \beta_3 JT_i S_i + \beta_4 MW_i E_i \\ & + \beta_5 JT_i^2 + \beta_6 MW_i^2 + \beta_7 JT_i^2 S_i + \beta_8 MW_i^2 E_i \\ & + \beta_9 JT_i^3 + \beta_{10} MW_i^3 + \beta_{11} JT_i^3 S_i + \beta_{12} MW_i^3 E_i + \gamma' X_i, \end{aligned}$$

and Φ denotes the c.d.f. of the standard normal distribution. The parameters of interest are in the first line: β_S and β_E, which identify the effects of severance pay and extended benefits.

[8]We control for age, age squared, experience, experience squared, gender, Austrian nationality, and four industry categories, log previous wage, and log previous wage squared.

Exit rates from non-employment. We model exits from unemployment as a discrete duration model where the probability of exiting in a given period is modeled as a probit. Again, we allow for third order polynomials in the running variables. We denote by $h_{ij}(t)$ the hazard of exiting non-employment in period t for the UI recipients ($j = I$) and non-recipients ($j = \bar{I}$). We consider discrete time intervals of variable length. That is, for unemployment durations up to 30 weeks we use intervals of 2 weeks, while above we fix intervals at 10 weeks. This accounts for two things. On the one hand, we have more observations for shorter durations which allows us to estimate the effects more precisely. On the other hand, it will be more crucial to have precisely estimated effects at shorter horizons for our structural analysis.

Our specification for the hazard of exiting unemployment reads

$$h_{ij}(t) = \Phi(\lambda_{ij}(t)), \tag{3.14}$$

where

$$\begin{aligned}\lambda_{ij}(t) =&\beta_{jS}S_i + \alpha_{jt}^S S_i + \beta_{jE}E_i + \alpha_{jt}^E E_i \\ &+ \beta_{j1}JT_i + \beta_{j2}MW_i + \beta_{j3}JT_i \times S_i + \beta_{j4}MW_i \times E_i \\ &+ \beta_{j5}JT_i^2 + \beta_{j6}MW_i^2 + \beta_{j7}JT_i^2 \times S_i + \beta_{j8}MW_i^2 \times E_i \\ &+ \beta_{j9}JT_i^3 + \beta_{j10}MW_i^3 + \beta_{j11}JT_i^3 S_i + \beta_{j12}MW_i^3 E_i \\ &+ \alpha_{jt} + \gamma_j' X_i.\end{aligned}$$

The parameters of interest are again in the first line: β_S identifies the effect of severance pay on the exit rate in period 0, while α_{jt}^S denotes the differential effect of severance pay on exit rates in period t (that is, the total effect of S_i on the exit rate in period t is $\beta_S + \alpha_{jt}^S$). The same holds for the effect of extended benefits. Thus, the effect of severance pay and extended benefits on exits from unemployment is allowed to change over the non-employment spell, which is consistent with theory. By including α_{jt}, we control for a piecewise constant baseline hazard of arbitrary form and thus account for duration dependence. X_i is a vector of observable characteristics[9]. In Appendix A, we give more details on the estimation procedure.

Selection around the discontinuity. Our main identification assumption is that all observable and unobservable worker characteristics evolve smoothly around the discontinuities defining eligibility for severance pay and extended benefits. While this cannot be tested directly, we can gain intuition on the validity of the assumption by checking

[9] We again control for age, age squared, experience, experience squared, gender, Austrian nationality, and four industry categories, log previous wage, and log previous wage squared.

whether the number of observations and observed characteristics display any salient features, in particular bunching or jumps, at the threshold. Much of the following has already been demonstrated by Card et al. (2007) and we will replicate much of their analysis to demonstrate that similar conclusions hold in our sample.

One threat to our identification would be that firms attempt to avoid mandatory severance payments by firing workers just before the three-year threshold. This behavior should show up as an excess mass just before and missing mass just after the eligibility threshold. As we can see from Figure 3.9(a) in Appendix B, however, we cannot discern any sign of strategic firing in the data. As argued by Card et al. (2007), this finding is not surprising as any such behavior is illegal and leads to bad reputation effects. For completeness, we also demonstrate that similar conclusions hold for the experience criterion as well (Figure 3.9(b)).

To investigate potential differences of observables around the discontinuity, we plot the average pre-displacement wage observed in our baseline sample by previous job tenure and the months worked in the preceding five years in Figure 3.10 in Appendix B. We conclude that there is no visible jump in either panel (a) or panel (b), suggesting that there is no differential selection around either discontinuity. This contrasts with the finding by Card et al. (2007), who find a small discontinuity in previous wages at the tenure threshold, but then argue that this discontinuity is negligible in terms of behavior. Our findings differ because we use a different baseline sample. In particular, we exclude workers below 25, whose jobs are often fixed-term (apprenticeships). In any case, mirroring the conclusion by Card et al. (2007), we conclude that there is no sign of quantitatively important selection around the discontinuities.

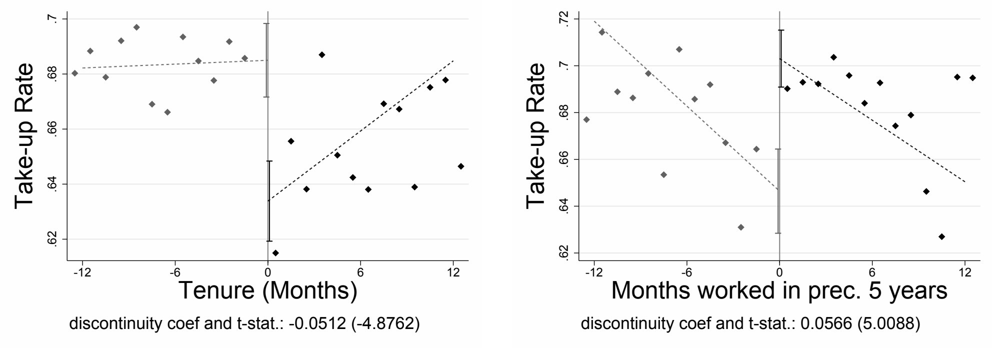
3.5 Empirical Findings

3.5.1 Descriptive Results

Take-up probability. To get an impression how the take-up rate and eligibility for severance pay and extended benefits correlate, we show descriptive discontinuity plots, based on local linear regressions of the form

$$p = \pi_0 + \pi_1 S + \pi_2 JT + \pi_3 JT \times S + \varepsilon,$$

for the effect of severance pay and analogously for the effect of extended benefits. For both regressions, we only include workers for whom the discontinuities do not coincide (effectively, this means $MW > JT$). We put more weight on observations close to the cutoff by using a triangular kernel following the suggestions by Porter (2003) and Hahn, Todd, and Van der Klaauw (2001). The reported t-statistics are based on a bootstrap with 1000 replications.



(a) Effect of SP

(b) Effect of EB

Figure 3.1: Effect on take-up of eligibility for severance pay and for extended benefits

Note: These figures plot average take-up rates per monthly tenure/experience bin. The lines correspond to local linear regressions estimates (individual level) on both sides separately and bootstrapped (1000 replications) confidence intervals, clustered by individual to account for correlation between spells.

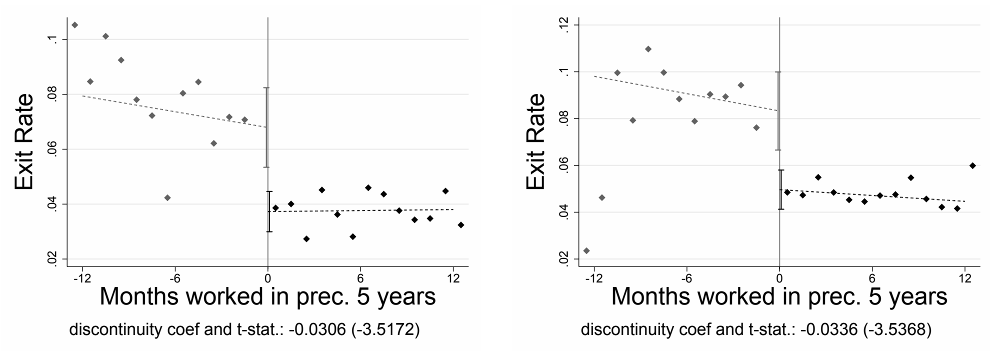
As predicted by theory, workers respond to a severance payment by claiming unemployment insurance less often—the take-up rate decreases by around 5.1% (Figure 3.1). The effect also goes into the right direction where extended benefits are concerned, as take-up increases by 5.7% at the discontinuity. These descriptive figures are only instructive, however, and a joint estimation of both discontinuities is needed, which we will conduct in the next section.

Exit rates from non-employment. One way of getting a graphical intuition for the effects of extended benefits on exits is by estimating regressions of the form

$$d(t) = \xi_0^t + \xi_1^t E + \xi_2^t MW + \xi_3^t MW \times E + \varepsilon,$$

where $d(t)$ is a dummy variable equal to 1 if a worker exits from non-employment in period t and we include all individuals having non-employment duration of at least t periods. Since we could produce a discontinuity plot for every period and running variable, we will concentrate on the most important moment for our identification, the effect of extended benefits on exits just before regular benefits run out, dh_{iIT-1}/dE_i.

Eligibility for extended benefits is likely to have stronger effects around the moment where regular benefits end. Figure 3.2 focuses on benefit recipients and looks at the effect of the extension two weeks before and after it takes place. There is a clearly discernible



(a) Claimants: Exit in weeks 19-20 (b) Claimants: Exit in weeks 21-22

Figure 3.2: Eligibility for extended benefits and probability of exiting before and after benefit extension

Note: These figures plot the probability of finding a job 19-20 weeks and 21-22 weeks after becoming unemployed, conditional on being unemployed for at least 18 weeks, for the claimants. The lines correspond to local linear regressions estimates (individual level) on both sides separately and bootstrapped (1000 replications) confidence intervals, clustered by individual to account for correlation between spells.

downward jump for the registered unemployed—the exit rate falls by over three percentage points from baseline level of around 7% and 8%.

3.5.2 Estimates

We estimate the model explained in Section 3.4.3, jointly considering both discontinuities, by maximum likelihood. We focus on individuals that are at most 12 months away from either cutoff. The standard errors are clustered at the individual level to account for unobserved correlation across various spells.

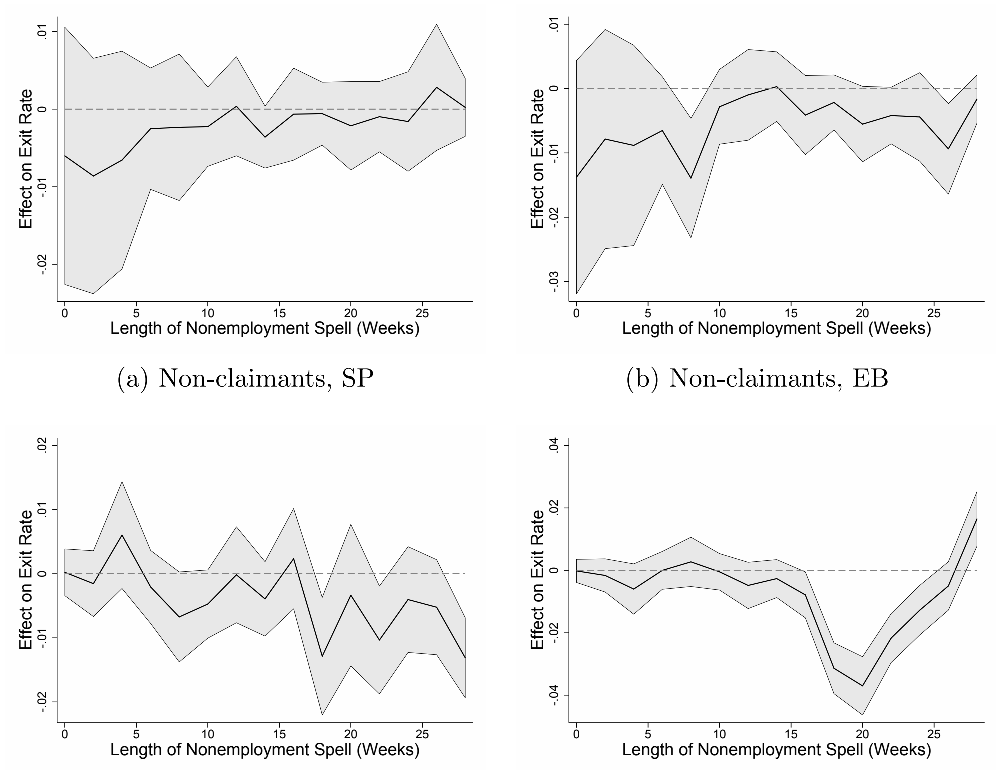
	(1) Baseline	(2) w/o Controls	(3) LPM	(4) $\geq$ 4 Layoffs by Firm
Severance Pay	-0.0747***	-0.0875***	-0.0699***	-0.101***
	(0.0183)	(0.0182)	(0.0166)	(0.0304)
Extended Benefits	0.0429**	0.0368**	0.0408**	0.0766**
	(0.0185)	(0.0183)	(0.0181)	(0.0301)
Observations	83451	83451	83451	30791

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
z-statistics (based on delta-method) in parentheses

Table 3.3: Effect of severance pay and extended benefits on take-up

Note: The numbers correspond to the predicted change in the take-up probability if either eligibility for severance pay or extended benefits are switched on. All running variables are set to 0, while covariates are set to their mean values. Standard errors are calculated using the delta method. Column 1 is calculated using the estimates from our baseline model. Column 2 replicates column 1 leaving out control variables X_i. In column 3, we replace the probit by a linear probability model we estimate by OLS. Column 4 restricts our sample to job separations resulting from mass layoffs, which we define as at least four layoffs within one month from the same firm.

The point estimates are shown in Table 3.7 in Appendix C. The marginal effects of becoming eligible for severance pay and extended benefits on the take-up probability are displayed in column 1 of Table 3.3. While we now control for both running variables simultaneously as well as for nonlinear terms and observed heterogeneity, the main conclusions of the descriptive analysis are unaffected. Eligibility for severance pay reduces the take-up probability by around 7 percent, while the effect of eligibility for extended benefits is positive, increasing the probability of collecting benefits by around 4 percent. We also probe the robustness of our results to the model assumptions in various ways: If we leave out control variables (column 2), the effects stay comparable. A classical RDD uses a linear specification—if we do so by estimating a linear probability model (column 3), the results do not change much, either. One concern might be that workers are fired selectively around the discontinuity. Even though we already concluded in Section 3.4.3 that there is no sign of selective firing, we can also address this question by focusing on mass layoffs: Arguably, layoffs involving multiple workers should correspond to an exogenous rather than to a selective displacement. If we conduct the same analysis focusing on workers having lost their job along with at least three other workers in the same month, we find even more pronounced effects (column 4).



(a) Non-claimants, SP (b) Non-claimants, EB

(c) Claimants, SP (d) Claimants, EB

Figure 3.3: Marginal effects over time

Note: The plots show the effect of becoming eligible for severance pay or extended benefits, respectively, on the probability of exiting unemployment over time. Covariates are fixed at their average value while the respective running variables are take at the threshold value. The confidence bands are based on standard errors clustered at the individual level.

We give a graphical representation of the effect on exit rates over time in Figure 3.3. Extended benefits affect exits negatively just before and after benefits run out for claimants, while non-claimants are unaffected. This is consistent with our model. The effect is stronger close to the benefit extension because workers account for the probability of exiting unemployment before the extension and because they discount the future. When entering unemployment, the value of the benefit extension is thus very small. It might be more surprising that we appear to find almost no effects of severance pay, while Card et al. (2007) document negative effects. While we use a different sample, the main reason is that we allow the effect of severance pay to change over the course of the spell, while they estimate the overall effect on the job finding hazard during the first 20 weeks of unemployment. In Appendix D, we demonstrate that we get comparable results if we use Card et al. (2007)'s strategy and look for an overall effect on exits during the first 20 weeks of unemployment.

We explore the robustness of our estimates in a similar way as for take-up by focusing on the effect of extended benefits on exits of claimants one period before the extension takes place, dh_{iIT-1}/dE_i, which is the moment featuring most prominently in our further analysis. Column 1 of Table 3.4 displays the marginal effect implied by our baseline estimates for period $T-1$ only. The probability of exiting during the last period before a benefit extension is predicted to decrease by around 3.2 percentage points, which, given a baseline probability of around 7% for the non-eligible, corresponds to a large effect. This estimate is not sensitive to either leaving out control variables or estimating a linear specification[10] (columns 2 and 3). If we restrict the sample to mass layoffs, the size of the effect decreases, but remains highly significant.

	(1) Baseline	(2) w/o Controls	(3) LPM	(4) $\geq$ 4 Layoffs by Firm
Extended Benefits	-0.0321***	-0.0322***	-0.0325***	-0.0201***
	(0.00415)	(0.00407)	(0.00417)	(0.00615)
Observations	83451	83451	83451	30791

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
z-statistics (based on delta-method) in parentheses

Table 3.4: Effect of severance pay and extended benefits on exits from unemployment one period before regular benefits run out ($T-1$)

Note: The numbers correspond to the predicted change in the probability of exiting unemployment (claimants) in the period before regular benefits run out if eligibility for extended benefits is switched on. All running variables are set to 0, while covariates are set to their mean values. Standard errors are calculated using the delta method. Column 1 is calculated using the estimates from our baseline model. Column 2 replicates column 1 leaving out control variables X_i. In column 3, we replace the probit by a linear probability model we estimate by OLS. See Appendix A for details. Column 4 restricts our sample to job separations resulting from mass layoffs, which we define as at least four layoffs within one month from the same firm.

One additional concern might be that there is heterogeneity driving both take-up and

[10] In Appendix A, we explain in detail how the linear approximation to our baseline model works.

job search, leading to correlation across the two margins. In Appendix E, we describe an estimator which allows for correlated unobserved heterogeneity between both decisions. As can be seen from Table 3.9 in Appendix E, we estimate a correlation across both decisions which is not statistically different from zero, and the parameter estimates are thus only marginally affected. Arguably, the observed covariates already do a sufficient job in controlling for correlation. If we estimate the same model without covariates, on the other hand, we estimate a strongly negative correlation between both decisions which is consistent with our model[11].

3.5.3 Implications

Estimation of the structural parameters. The econometric model, along with the estimated parameters, gives us predictions for the effect of extended benefits on take-up and on exits from unemployment based on individual characteristics. Call v_E the cash value of extended benefits and denote by E_i whether individual i is eligible for extended benefits. The estimated marginal effects can be connected to the theoretical effects by realizing that

$$\frac{dh_{iIT-1}}{dE_i} \approx \frac{ds_{iIT-1}}{db^e} v_E$$
$$\frac{dp_i}{dE_i} \approx \frac{d\ell_i}{db^e} v_E.$$

Combining these results, we obtain

$$M_i = \frac{d\ell_i/db^e}{ds_{iIT-1}/db^e} \approx \frac{dp_i/dE_i}{dh_{iIT-1}/dE_i}.$$

The ultimate goal is to solve for the parameters in equation (3.12), by solving

$$\{\theta, a\} = \arg\min \sum_i \left(\ln(-M_i) - \ln \left(f\left(F^{-1}(p_i)\right) \beta^{T-2} \left(\prod_{\tau=1}^{T-1} (1 - s_{I\tau}) \right) \psi_i''(s_{iIT-1}) \right) \right)^2.$$

To make progress, we assume that take-up costs ϕ are Weibull distributed. Other distributions are possible but the Weibull distribution is flexible and it has delivered the

[11]The results are available on request.

best fit to the empirical moments[12]. Letting $\Delta_i \equiv U^I_{i0} - U^{\bar{I}}_{i0}$, this assumption implies

$$\ell_i = F(\Delta_i) = 1 - \exp\left(-(\Delta_i/\theta_{i0})^{\theta_1}\right),$$

where $\{\theta_0, \theta_1\}$ are the parameters of the cost distribution to be estimated. We also assume that the search cost function is isoelastic, satisfying $\psi(s) = a_{0i}s^{a_1}$. We account for observed heterogeneity by assuming $a_{0i} = a_0 \exp(X_i'\xi)$ and $\theta_{0i} = \theta_0 \exp(X_i'\pi)$, where X_i is a vector of covariates.

In Appendix F, we show that, given our assumptions, we obtain the following estimable equation

$$y_i = K + \frac{\theta_1 - 1}{\theta_1} \ln(-\ln(1 - p_i)) + (a_1 - 2) \ln h_{iIT-1} + X_i'\gamma, \tag{3.15}$$

where $\gamma \equiv \xi - \pi$, $y_i \equiv \ln \frac{dp_i}{dE_i} - \ln\left(-\frac{dh_{iIT-1}}{dE_i}\right) - \ln(1 - p_i) - \ln\left(\prod_{\tau=1}^{T-1}(1 - h_{iI\tau})\right)$ and $K \equiv \ln \frac{\theta_1}{\theta_0} + \ln \beta^{T-2} + \ln(a_0 a_1(a_1 - 1))$.

By estimating (3.15) by OLS, we get estimates of the shape parameter of the take-up cost distribution, θ_1, as well as of the curvature of the search cost function, a_1. By controlling for X_i, we effectively control for how observables drive the relative importance of the take-up and the search margin. ξ and π are not separately identified but separate identification is not necessary to compute our metric. β is not identified separately, either, and we will have to calibrate it later on.

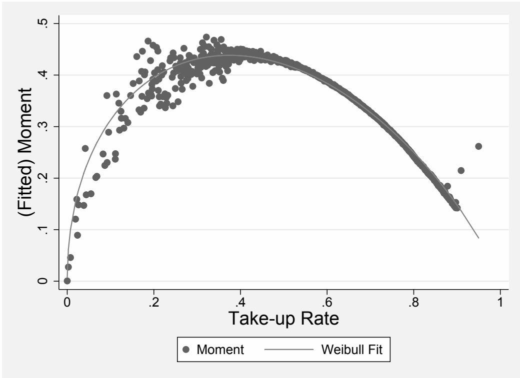
	Estimate	95% CI (Delta Method)
θ_1	1.886	[1.411,2.360]
a_1	1.872	[1.862,1.882]

Table 3.5: Implied structural parameters

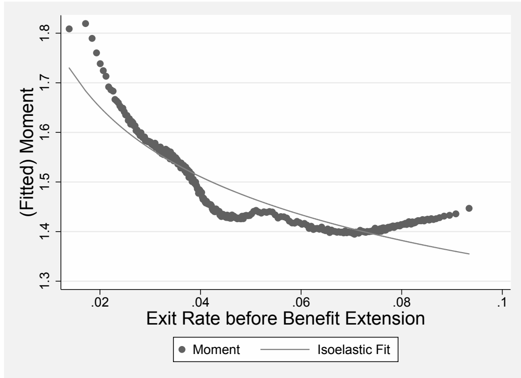
The regression results are shown in Table 3.8 in Appendix C, while Table 3.5 lists the implied structural parameters. Search costs are almost quadratic, which is consistent with previous work (see, e.g., Yashiv (2000) (Israeli data) and Christensen et al. (2005) (Danish data)). The Weibull distribution reduces to the exponential distribution for $\theta_1 = 1$, which can be rejected. The R^2 is above 95%, which suggests that the parametric assumptions do a good job in describing the data. Figure 3.4 gives an additional sense of how well our specification fits the data: We rewrite (3.15) so as to isolate either p_i or h_{iIT-1} on the right-hand side and then plot the right-hand side against the left-hand side.

In Figure 3.4(a), we can see that the Weibull distribution succeeds in describing the hump-shaped relationship between the take-up rate and the empirical moment. It makes

[12]We have also come up with a strategy which does not rely on any distributional assumption. The results are almost unaffected, which is due to the fact that the Weibull already fits the empirical moments very well. We thus decided to stick with the more parsimonious parametric approach.



(a) Weibull fit



(b) Isoelastic fit

Figure 3.4: Fit of the Weibull and isoelastic specification to the empirical moments

Note: In the left figure we asses the fit of of he Weibull distribution to the empirical moments by plotting $\exp(y_i + \ln(1 - p_i) - \hat{K} - (\hat{a}_1 - 2)\ln h_{iIT-1} - X_i'\hat{\gamma})$ (gray dots) against $\exp(((\hat{\theta}_1 - 1)/\hat{\theta}_1)\ln(-\ln(1-p_i)) + \ln(1-p_i))$ (red line), where hats denote estimated coefficients, based on equation (3.15). In the right figure we asses the fit of the isoelastic search cost by plotting $\exp(y_i - \hat{K} - ((\hat{\theta}_1 - 1)/\hat{\theta}_1)\ln(-\ln(1-p_i) - X_i'\hat{\gamma})$ (gray dots) against $\exp((\hat{a}_1 - 2)\ln h_{iIT-1})$ (red line), where hats denote estimated coefficients, based on equation (3.15). In the left figure, the dots correspond to averages within take-up rate bins of width 0.001. The dots in the right figure correspond to means within 300 quantiles of the exit rate (to take care of outliers).

sense that the reaction of take-up is strongest for a take-up probability around 50%, while most observations are in the downward sloping part. The downward sloping line in Figure 3.4(b) is due to an estimated elasticity of search costs of less than two (quadratic search costs would imply a flat relationship). This implies a slightly stronger reaction of search effort if the exit rate is already high.

The value of unemployment insurance. We are now able to calculate bounds on the value of unemployment insurance, using our estimates for the marginal effects, the estimates of the structural parameters and equations (3.10) and (3.11) for the bounds. In order to connect empirical estimates to theoretical marginal effects, we use the approximation

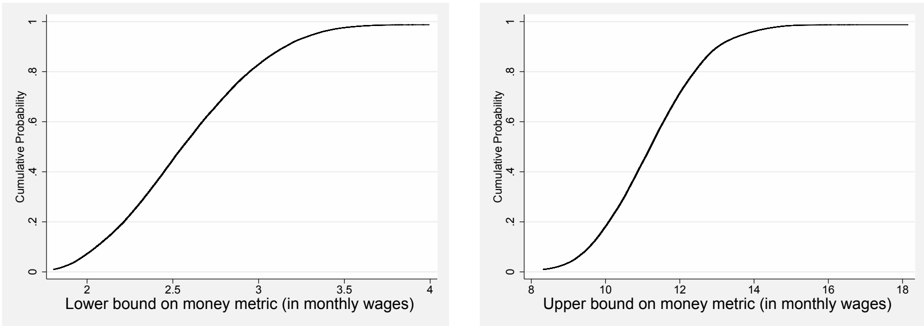
$$\frac{dp_i}{dS_i} \approx \frac{d\ell_i}{dA_0} v_S$$
$$\frac{dh_{iIT-1}}{dE_i} \approx \frac{ds_{iIT-1}}{db^e} v_E,$$

where S_i and E_i indicate eligibility for severance pay and extended benefits, respectively, and v_S and v_E denote the cash value of severance pay and extended benefits. In Appendix F, we show the exact expressions for the bounds we implement.

Following Card et al. (2007), we assume that $v_E \approx 0.85w$ and $v_S \approx 2.69w$, where w is the after-tax individual monthly wage[13]. In order to implement our formula, we need to

[13]The value of extended benefits is an approximation because one needs to account for unemployment assistance to compute this value and the benefits of UA depends on the household earnings that we do

translate v_E to one period in our empirical model. Since the extension affects five two-weekly periods, we use $v_E = (0.85/5)w = 0.17w$. For the baseline results, we assume an annual discount rate of 5%. While this has no effect by construction on the upper bound for claimants and the lower bound for non-claimants, we show in Table 3.6 in Appendix B that alternative assumptions have a negligible effect on the other bounds.



(a) Lower bound (b) Upper bound

Figure 3.5: Bounds on wealth transfer to claimants

Note: The plots show c.d.f.'s of the lower and upper bound on ΔA based on equations (3.10) and (3.11), for claimants of UI. ΔA is the asset transfer to a non-claimant required to make her indifferent between claiming and not claiming. It is a monetary equivalent to the difference in intertemporal utilities between claimants and non-claimants net of claiming costs and thus is, by construction, positive for claimants and negative for non-claimants. We only display observations between the 1st and the 99th percentile.

In Figure 3.5, we plot the distribution of the resulting lower and upper bounds for claimants, who have a positive ΔA. We find that for the median individual the relative value of collecting benefits net of claiming costs is equivalent to at least 2.5 monthly wages. This is the minimum amount, implied by her behavioral responses to severance pay and extended benefits, which one needs to transfer when she enters unemployment so as to make her indifferent between collecting benefits or not. The lower bound appears reasonable given a quick back-of-the-envelope calculation: The median number of weeks unemployed among the claimants with unemployment duration in our baseline sample is 23. With a replacement rate of 0.55, the expected total sum of UI payments (ignoring discounting) is $(23/52) \cdot 12 \cdot 0.55 = 2.92$ monthly wages for those eligible for extended benefits and $(20/52) \cdot 12 \cdot 0.55 = 2.54$ for the non-eligible. Our metric also accounts for take-up cost, discounting and non-monetary benefits of collecting benefits but this shows that our lower bound is a credible estimate of the value of the insurance and its distribution. The upper bound, around 11 monthly wages for the median, appears on the contrary less informative.

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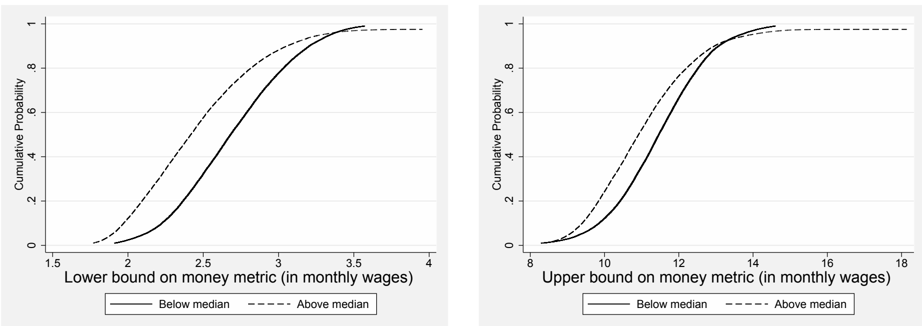
not observe. As in Card et al. (2007), we assume that the individual has a partner with a net wage of 1200 euros per month and two children.

(a) Lower bound (b) Upper bound

Figure 3.6: Bounds on wealth transfer to non-claimants

Note: The plots show c.d.f.'s of the lower and upper bound on ΔA based on equations (3.10) and (3.11), for non-claimants of UI. See notes of Figure 3.5 for further details. We only display observations between the 1st and the 99th percentile.

The results for non-claimants are shown in Figure 3.6. Their relative value of UI net of claiming costs is negative, meaning they would be willing to give up part of their wealth to avoid having to claim for UI. We find that the median individual would have to lose the equivalent of *at least* 2 monthly wages to become claimant. Again the other bound, above nine months for the median, appears less informative. In any case, even just focusing on the first bound, these numbers suggest that the perceived take-up costs are sizable for many workers who don't collect, caused by, for instance, a combination of intrinsic aversion to the welfare state (induced by stigma for example), administrative costs of filling a claim and the set of constraints imposed on those who collect benefits.

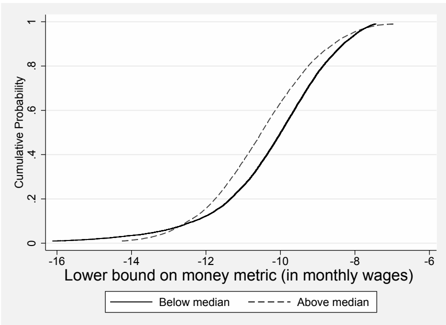


(a) Lower bound (b) Upper bound

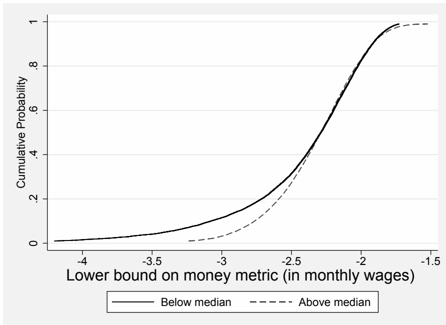
Figure 3.7: Bounds on wealth transfer to claimants by previous wage

Note: The plots show c.d.f.'s of the lower and upper bound on ΔA based on equations (3.10) and (3.11), for claimants of UI, according to whether the previous wage was above or below the median. See notes of Figure 3.5 for further details. We only display observations between the 1st and the 99th percentile.

It is interesting to see if the value of unemployment insurance varies with worker characteristics, especially for the claimants. Figure 3.7 displays the distribution of the lower and upper bound of claimants, distinguishing between high- (above median) and low-wage (below median) workers. Except for very high values, the distribution of values for workers below median stochastically dominates the distribution of values for the workers above. This means that the value of the insurance is higher for low-wage workers. Closer inspection of this finding in the data reveals that this is mostly driven by a higher estimated take-up probability among low-wage workers. A high take-up probability is indicative of a high difference in intertemporal utilities between claiming and not claiming. Finally, the same exercise can be done for those who don't collect benefits (Figure 3.8), but there are no clear results here. While the low-wage workers seem to be willing to give up less in order to avoid claiming where the lower bound is concerned, this relationship switches or disappears for the upper bound.



(a) Lower bound



(b) Upper bound

Figure 3.8: Bounds on wealth transfer to non-claimants by previous wage

Note: The plots show c.d.f.'s of the lower and upper bound on ΔA based on equations (3.10) and (3.11), for non-claimants of UI, according to whether the previous wage was above or below the median. See notes of Figure 3.5 for further details. We only display observations between the 1st and the 99th percentile.

3.6 Conclusion

Using variation in take-up and job search behavior, this paper infers bounds on the value of unemployment insurance. Using Austrian administrative data and a double discontinuity, one in the eligibility for severance pay, one in the eligibility for extended unemployment benefits, we first document the fact that the probability of claiming is lower if workers are eligible for severance pay, which is equivalent to a wealth shock when entering unemployment. On the contrary, eligibility for extended benefits increases the take-up probability and lowers the exits from unemployment around the time where the extension occurs. Then, using a simple job search model where workers face a cost of claiming for unemployment benefits, we show that these results can be used to derive bounds on the insurance value. For the workers who collect benefits, we show that the median value of the insurance is at least equal to a transfer of 2.5 monthly wages at the beginning of the unemployment spell. Interestingly, the value of the insurance is higher for low wage workers. For the workers who don't claim, the value is by definition negative with an upper bound of around two monthly wages for the median individual. This suggests that, for a significant share of the individuals, take-up costs, stigma and/or constraints imposed on those who collect are sizable.

Acknowledgements

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3.7 Appendix

A Details on the Discrete Duration Model

As noticed early, discrete time duration model can conveniently be estimated as binary models (see Allison (1982) or Jenkins (1995)). Let t denote unemployment duration. Individual i's likelihood contribution is then given by

$$\ell_i = \left[\Pr\left(T_i = t_i\right)\right]^{d_i} \left[\Pr\left(T_i > t_i\right)\right]^{1-d_i},$$

where d_i takes the value 1 if i's observation is non-censored. As described in the main text, we denote by $h_{ij}(t)$ the hazard of individual i with take-up status $j \in \left\{I, \bar{I}\right\}$ of exiting unemployment in period t. We obtain

$$\begin{aligned}
\ell_i &= \left[h_{ij}(t) \prod_{s=1}^{t_i-1}(1-h_{ij}(s))\right]^{d_i} \left[\prod_{s=1}^{t_i}(1-h_{ij}(s))\right]^{1-d_i} \\
&= \left[\frac{h_{ij}(t_i)}{1-h_{ij}(t_i)}\right]^{d_i} \prod_{s=1}^{t_i}(1-h_{ij}(s))
\end{aligned}$$

and hence

$$\begin{aligned}
\log \ell_i &= d_i \log\left(\frac{h_{ij}(t)}{1-h_{ij}(t)}\right) + \sum_{s=1}^{t_i} \log(1-h_{ij}(s)) \\
&= \sum_{s=1}^{t_i} y_{it} \log\left(\frac{h_{ij}(s)}{1-h_{ij}(s)}\right) + \sum_{s=1}^{t_i} \log(1-h_{ij}(s)),
\end{aligned}$$

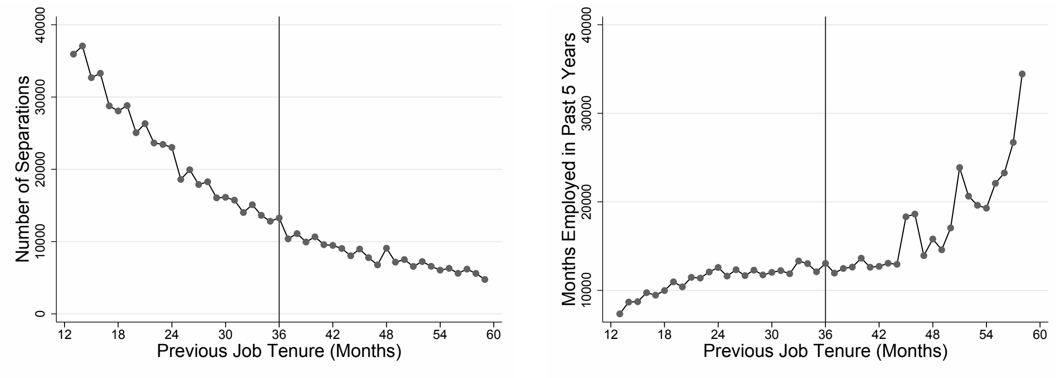
where y_{it} is a dummy which takes the value 1 if individual i exits in period t. The log-likelihood is then

$$\mathcal{L} = \sum_{i=1}^{N} \sum_{s=1}^{t_i} y_{it} \log(h_{ij}(s)) + \sum_{i=1}^{N} \sum_{s=1}^{t_i} (1-y_{it}) \log(1-h_{ij}(s)).$$

Looking closely at the resulting expression, we realize that it is equivalent to a set of binary regressions for $1, \ldots, t_i$. Estimation of the duration model amounts to treating periods $1, \ldots, t_i$ for each individual as separate observations and setting the dependent variable y_{it} equal to 1 if individual i exits in t and 0 otherwise. Choosing a functional form for $h_{ij}(t)$, we estimate the resulting model by maximum likelihood.

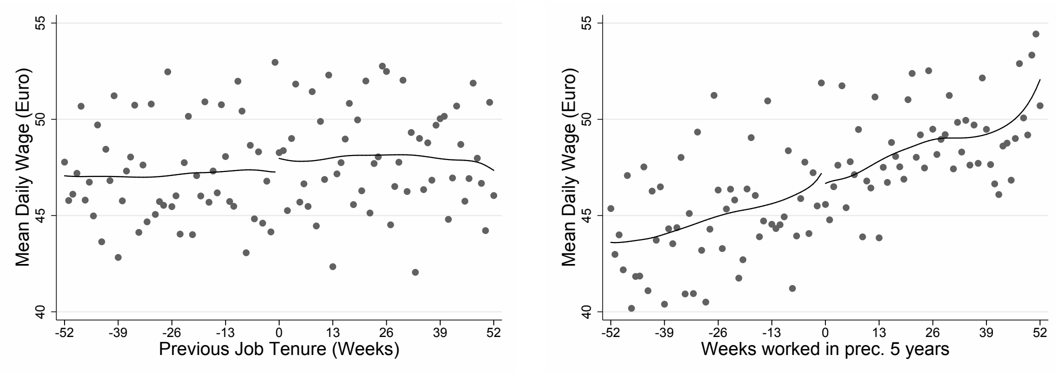
In our baseline specification, we assume $h_{ij}(t)$ to be of probit form. This naturally restricts the probability to be between zero and one and it enables to introduce correlated unobserved heterogeneity as robustness exercise. In our result tables, we also present the results in the case where we assume $h_{ij}(t)$ to be linear, estimating the resulting specification by OLS. This is what we call "LPM" in Table 3.4.

B Additional Figures and Tables



(a) By Job Tenure (b) By Months Worked

Figure 3.9: Frequency of Separations by Job Tenure



(a) By Job Tenure (b) By Months Worked

Figure 3.10: Previous Wage according to Previous Job Tenure and Months Worked in Preceding 5 Years

Annual Discount Rate	1 %	5 %	10 %	20 %
Upper Bound (Non-Claimants)	-2.321	-2.293	-2.259	-2.198
Lower Bound (Claimants)	2.580	2.549	2.512	2.445

Table 3.6: Different assumptions on the annual discount rate and implied median values for the bounds

C Estimation Results

	(1) Exit uninsured	(2) Exit insured	(3) Take-up
Severance Pay	-0.0319	0.00467	-0.194***
	(0.0446)	(0.0394)	(0.0473)
Severance Pay × Period 1	-0.0197	-0.0258	
	(0.0368)	(0.0413)	
Severance Pay × Period 2	-0.0122	0.0418	
	(0.0393)	(0.0384)	
Severance Pay × Period 3	-0.00394	-0.0299	
	(0.0503)	(0.0412)	
Severance Pay × Period 4	0.00420	-0.0676*	
	(0.0504)	(0.0396)	
Severance Pay × Period 5	-0.0243	-0.0690	
	(0.0600)	(0.0430)	
Severance Pay × Period 6	0.0389	-0.00625	
	(0.0545)	(0.0410)	
Severance Pay × Period 7	-0.0859	-0.0553	
	(0.0653)	(0.0439)	
Severance Pay × Period 8	0.0176	0.0172	
	(0.0614)	(0.0423)	
Severance Pay × Period 9	0.00977	-0.110**	
	(0.0746)	(0.0448)	
Severance Pay × Period 10	-0.0195	-0.0269	
	(0.0666)	(0.0430)	
Severance Pay × Period 11	-0.00186	-0.0997**	
	(0.0772)	(0.0456)	
Severance Pay × Period 12	-0.0000625	-0.0420	
	(0.0610)	(0.0445)	
Severance Pay × Period 13	0.0793	-0.0590	
	(0.0617)	(0.0450)	
Extended Benefits	-0.0707	-0.00377	0.118**
	(0.0471)	(0.0400)	(0.0509)
Extended Benefits × Period 1	0.0266	-0.0182	
	(0.0361)	(0.0395)	
Extended Benefits × Period 2	0.0144	-0.0454	
	(0.0385)	(0.0370)	
Extended Benefits × Period 3	-0.0190	0.00376	
	(0.0489)	(0.0395)	
Extended Benefits × Period 4	-0.102**	0.0272	
	(0.0483)	(0.0379)	
Extended Benefits × Period 5	0.00626	-0.00221	
	(0.0592)	(0.0410)	
Extended Benefits × Period 6	0.0534	-0.0426	
	(0.0543)	(0.0393)	
Extended Benefits × Period 7	0.0786	-0.0293	
	(0.0641)	(0.0417)	
Extended Benefits × Period 8	-0.0193	-0.0750*	
	(0.0604)	(0.0405)	
Extended Benefits × Period 9	-0.00838	-0.290***	
	(0.0731)	(0.0409)	
Extended Benefits × Period 10	-0.0598	-0.292***	
	(0.0632)	(0.0402)	
Extended Benefits × Period 11	-0.0790	-0.214***	
	(0.0745)	(0.0423)	
Extended Benefits × Period 12	-0.0143	-0.122***	
	(0.0596)	(0.0425)	
Extended Benefits × Period 13	-0.109*	-0.0474	
	(0.0606)	(0.0434)	
Log-Likelihood	-66356.567	-159209.240	-51777.868
Observations	83451	83451	83451

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

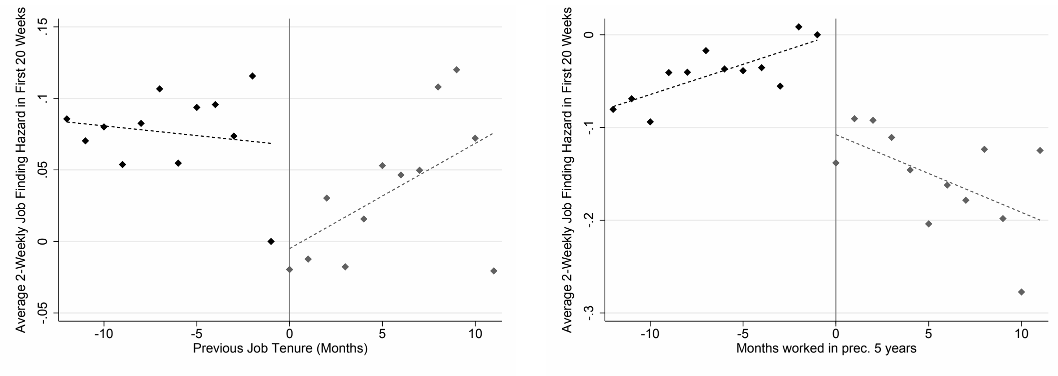
Table 3.7: Effect of severance pay and extended benefits on exits from unemployment and take-up

	Estimate	95% CI
$\ln(-\ln(1-p_i))$	0.470	[0.336,0.603]
$\ln h_{iIT-1}$	-0.128	[-0.138,-0.118]
Observations	83451	
R^2	0.953	

95% confidence intervals (robust to heteroskedasticity) in brackets.

Table 3.8: Regression results (equation (3.15))

D The Effect of Severance Pay and Extended Benefits on Exits during the First 20 Weeks



(a) Effect of SP

(b) Effect of EB

Figure 3.11: Effect of severance pay and benefit extension on exits from unemployment during the first two weeks among claimants

In this section, we show that we obtain similar conclusions if we apply Card et al. (2007)'s strategy to our dataset. In particular, in order to estimate the effect of eligibility for SP on overall exits from unemployment during the first 20 weeks, we censor all observations with unemployment duration above 20 weeks. We then estimate

$$h(t) = \exp(\lambda_t),$$

where

$$\begin{aligned}\lambda_t = \alpha_t + \theta_1 \mathbb{1}\left[JT = -12\right] + \ldots + \theta_{11} \mathbb{1}\left[JT = -2\right] \\ + \theta_{13} \mathbb{1}\left[JT = 0\right] + \ldots + \theta_{24} \mathbb{1}\left[JT = 12\right] \\ + \beta_1 E + \beta_2 MW + \beta_3 MW \times E + \beta_4 MW^2 + \beta_5 MW^2 \times E \\ + \beta_6 MW^3 + \beta_7 MW^3 \times E,\end{aligned}$$

and t is in discrete time with two-weekly intervals and α_t controls for the baseline hazard. Note that $JT = -1$ is the omitted category. The θs hence give us the difference in the two-weekly job-finding probability relative to an individual just below the eligibility threshold for SP. We can do the analogous analysis for the effect of EB.

We plot the estimated θs in Figure 3.11. The discontinuities are roughly comparable in size to Card et al. (2007), who report an effect between -0.094 and -0.125 for SP and -0.064 and -0.093 for EB.

E Allowing for Correlated Unobserved Heterogeneity in Take-up and Search Effort Choices

Assume the probability of claiming UI can be represented by the following equation

$$\ell_i = \text{Prob}\left\{\theta_i^\ell + \varepsilon_i^\ell > 0\right\}$$

where

$$\begin{aligned}\theta_i^\ell =& \beta_S S_i + \beta_E E_i + \beta_1 JT_i + \beta_2 MW_i + \beta_3 JT_i S_i + \beta_4 MW_i E_i \\ &+ \beta_5 JT_i^2 + \beta_6 MW_i^2 + \beta_7 JT_i^2 S_i + \beta_8 MW_i^2 E_i + \gamma' X_i.\end{aligned}$$

Moreover, the probability that a job is found in period t, given that i is unemployed up to period t, for take-up status $j \in \{0, 1\}$, is given by

$$\lambda_{ij}(t) = \text{Prob}\left\{\theta_{ij}^\lambda(t) + \varepsilon_i^\lambda > 0\right\}, \tag{3.16}$$

where

$$\begin{aligned}\theta_{ij}^\lambda(t) =& \beta_S S_i + \sum_{\tau=1}^{T} \alpha_\tau^S \mathbb{1}[t=\tau] \times S_i + \beta_E E_i + \sum_{\tau=1}^{T} \alpha_\tau^E \mathbb{1}[t=\tau] \times E_i \\ &+ \beta_1 JT_i + \beta_2 MW_i + \beta_3 JT_i \times S_i + \beta_4 MW_i \times E_i \\ &+ \beta_5 JT_i^2 + \beta_6 MW_i^2 + \beta_7 JT_i^2 \times S_i + \beta_8 MW_i^2 \times E_i + \\ &+ \beta_9 JT_i^3 + \beta_{10} MW_i^3 + \beta_{11} JT_i^3 \times S_i + \beta_{12} MW_i^3 \times E_i + \gamma' X_i,\end{aligned}$$

where we suppressed the dependence of all parameters on j to simplify notation.

To capture unobserved heterogeneity correlated across decisions, we assume that

$$\begin{bmatrix}\varepsilon_i^\ell \\ \varepsilon_i^\lambda\end{bmatrix} |(\theta_i^\ell, \theta_{ij}^\lambda) \sim \mathcal{N}\left(\begin{bmatrix}0 \\ 0\end{bmatrix}, \begin{bmatrix}1 & \rho \\ \rho & 1\end{bmatrix}\right).$$

For identifiability, we need to assume that ε_i^λ's conditional distribution does not depend on the takeup-status.

Consider worker i and assume i claims UI and exits after t_i periods. His contribution to the log-likelihood is given by

$$\begin{aligned}
\ln \operatorname{Prob}\left\{\theta_i^\ell + \varepsilon_i^\ell > 0\right\} \\
&+ \sum_{\tau=1}^{t_i-1} \ln\left(1 - \operatorname{Prob}\left\{\theta_{ij}^\lambda(\tau) + \varepsilon_i^\lambda > 0 | \theta_i^\ell + \varepsilon_i^\ell > 0\right\}\right) \\
&\qquad + \ln \operatorname{Prob}\left\{\theta_{ij}^\lambda(t) + \varepsilon_i^\lambda > 0 | \theta_i^\ell + \varepsilon_i^\ell > 0\right\}.
\end{aligned}$$

Using the properties of the bivariate normal distribution, this is equivalent to

$$\ln \Phi(\theta_i^\ell) + \sum_{\tau=1}^{t_i-1} \ln\left(\frac{\Phi_2(-\theta_{ij}^\lambda(\tau), \theta_i^\ell, -\rho)}{\Phi(\theta_i^\ell)}\right) + \ln\left(\frac{\Phi_2(\theta_{ij}^\lambda(t), \theta_i^\ell, \rho)}{\Phi(\theta_i^\ell)}\right),$$

where Φ_2 denotes the c.d.f. of the bivariate normal distribution.

Define f_{it} which takes the value 1 if i exits in period t and 0 otherwise. Then, the likelihood contribution can be written as $\sum_1^{t_i} l_{i\tau}$, where

$$l_{i\tau} = \mathbb{1}\left\{\tau = 1\right\} \cdot \ln \Phi(\theta_i^\ell) + (1 - f_{it}) \ln\left(\frac{\Phi_2(-\theta_{ij}^\lambda(\tau), \theta_i^\ell, -\rho)}{\Phi(\theta_i^\ell)}\right) + f_{it} \ln\left(\frac{\Phi_2(\theta_{ij}^\lambda(\tau), \theta_i^\ell, \rho)}{\Phi(\theta_i^\ell)}\right).$$

More generally, let $q_i^\ell = 2 \cdot \ell_i - 1$ and $q_i^{fj} = 2 \cdot f_{it}^j - 1$ for $j \in \{0, 1\}$. Then the likelihood contribution of period τ of worker i is given by

$$l_{i\tau} = \mathbb{1}\left\{\tau = 1\right\} \cdot \ln \Phi(q_i^\ell \theta_i^\ell) + \ln\left(\frac{\Phi_2(q_i^{fj} \theta_{ij}^\lambda(\tau), q_i^\ell \theta_i^\ell, q_i^\ell q_i^{fj} \rho)}{\Phi(q_i^\ell \theta_i^\ell)}\right).$$

If we impose $\rho = 0$, we obtain our baseline model as a special case.

	Exit uninsured	Exit insured	Take-up
Severance Pay	-0.0511	-0.00908	-0.196***
	(0.0785)	(0.0575)	(0.0478)
Severance Pay × Period 1	-0.0196	-0.0258	
	(0.0365)	(0.0411)	
Severance Pay × Period 2	-0.0122	0.0414	
	(0.0390)	(0.0383)	
Severance Pay × Period 3	-0.00406	-0.0298	
	(0.0499)	(0.0410)	
Severance Pay × Period 4	0.00395	-0.0674*	
	(0.0500)	(0.0394)	
Severance Pay × Period 5	-0.0243	-0.0688	
	(0.0596)	(0.0429)	
Severance Pay × Period 6	0.0384	-0.00629	
	(0.0542)	(0.0409)	
Severance Pay × Period 7	-0.0855	-0.0551	
	(0.0649)	(0.0437)	
Severance Pay × Period 8	0.0173	0.0170	
	(0.0609)	(0.0422)	
Severance Pay × Period 9	0.00953	-0.110**	
	(0.0741)	(0.0446)	
Severance Pay × Period 10	-0.0196	-0.0269	
	(0.0661)	(0.0428)	
Severance Pay × Period 11	-0.00159	-0.0994**	
	(0.0766)	(0.0454)	
Severance Pay × Period 12	-0.000233	-0.0418	
	(0.0605)	(0.0443)	
Severance Pay × Period 13	0.0785	-0.0587	
	(0.0614)	(0.0448)	
Extended Benefits	-0.0585	0.00431	0.117**
	(0.0635)	(0.0468)	(0.0510)
Extended Benefits × Period 1	0.0264	-0.0181	
	(0.0359)	(0.0393)	
Extended Benefits × Period 2	0.0144	-0.0451	
	(0.0382)	(0.0369)	
Extended Benefits × Period 3	-0.0188	0.00377	
	(0.0486)	(0.0393)	
Extended Benefits × Period 4	-0.101**	0.0272	
	(0.0483)	(0.0378)	
Extended Benefits × Period 5	0.00634	-0.00211	
	(0.0588)	(0.0408)	
Extended Benefits × Period 6	0.0532	-0.0423	
	(0.0540)	(0.0391)	
Extended Benefits × Period 7	0.0782	-0.0291	
	(0.0637)	(0.0416)	
Extended Benefits × Period 8	-0.0191	-0.0746*	
	(0.0600)	(0.0404)	
Extended Benefits × Period 9	-0.00825	-0.288***	
	(0.0726)	(0.0417)	
Extended Benefits × Period 10	-0.0592	-0.291***	
	(0.0629)	(0.0410)	
Extended Benefits × Period 11	-0.0783	-0.213***	
	(0.0741)	(0.0427)	
Extended Benefits × Period 12	-0.0141	-0.121***	
	(0.0592)	(0.0425)	
Extended Benefits × Period 13	-0.108*	-0.0471	
	(0.0605)	(0.0433)	
Estimated Correlation	.1401(.466)		
Log-Likelihood	-277343.452		
Observations	83451		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: Effect of severance pay and extended benefits on exits from unemployment and take-up, allowing for unobserved heterogeneity

F Omitted Results

Derivation of the estimable equation

Letting $\Delta_i \equiv U^I_{i0} - U^{\bar{I}}_{i0}$ and assuming ϕ is Weibull distributed, the take-up probability satisfies

$$\ell_i = F(\Delta_i) = 1 - \exp\left(-(\Delta_i/\theta_{0i})^{\theta_1}\right),$$

where $\{\theta_{0i}, \theta_1\}$ are the parameters of the cost distribution to be estimated. Inverting this relationship, we find

$$\Delta_i = F^{-1}(\ell_i) = \theta_{0i}\left[-\ln(1-\ell_i)\right]^{1/\theta_1}.$$

Since the p.d.f. satisfies

$$f(\Delta_i) = \frac{\theta_1}{\theta_{0i}}\left(\frac{\Delta_i}{\theta_{0i}}\right)^{\theta_1 - 1}\exp\left(-(\Delta_i/\theta_{0i})^{\theta_1}\right),$$

we conclude

$$f\left(F^{-1}(\ell_i)\right) = \frac{\theta_1}{\theta_{0i}}\left[-\ln(1-\ell_i)\right]^{\frac{\theta_1-1}{\theta_1}}(1-\ell_i).$$

Moreover, assuming that the search cost function is isoelastic, satisfying $\psi(s) = a_{0i}s^{a_1}$, we obtain

$$\psi''(s) = a_{0i}a_1(a_1-1)s^{a_1-2}.$$

Plugging into the regression equation and replacing theoretical by estimated values, we find

$$\ln\frac{dp_i}{dE_i} - \ln\left(-\frac{dh_{iIT-1}}{dE_i}\right) = \ln\frac{\theta_1}{\theta_{0i}} + \frac{\theta_1-1}{\theta_1}\ln(-\ln(1-p_i)) + \ln(1-p_i) + \ln\beta^{T-2} + \ln\left(\prod_{\tau=1}^{T-1}(1-h_{iI\tau})\right) + \ln(a_{0i}a_1(a_1-1)) + (a_1-2)\ln h_{iIT-1}.$$

We account for observed heterogeneity by assuming $a_{0i} = a_0\exp(X_i'\xi)$ and $\theta_{0i} = \theta_0\exp(X_i'\pi)$, where X_i is a vector of covariates. Define $\gamma \equiv \xi - \psi$. Simplifying and collecting terms, we get the estimable equation

$$y_i = K + \frac{\theta_1-1}{\theta_1}\ln(-\ln(1-p_i)) + (a_1-2)\ln h_{iIT-1} + X_i'\gamma, \tag{3.17}$$

where $y_i \equiv \ln\frac{dp_i}{dE_i} - \ln\left(-\frac{dh_{iIT-1}}{dE_i}\right) - \ln(1-p_i) - \ln\left(\prod_{\tau=1}^{T-1}(1-h_{iI\tau})\right)$ and $K \equiv \ln\frac{\theta_1}{\theta_0} + \ln\beta^{T-2} + \ln(a_0a_1(a_1-1))$.

Implementation of Bounds on Money Metric

Following the results derived by McEwen and Parresol (1991) for the truncated Weibull distribution, the expected take-up cost can be written as

$$\bar{\phi} = \begin{cases} \theta_0 \frac{\gamma(1/\theta_1+1,-\ln(1-p_i))}{p_i} & \text{if registered,} \\ \theta_0 \frac{\Gamma(1/\theta_1+1)-\gamma(1/\theta_1+1,-\ln(1-p_i))}{1-p_i} & \text{if not registered,} \end{cases}$$

where $\Gamma(z) \equiv \int_0^\infty x^{z-1} \exp(-x)\, dx$ denotes the Gamma function and $\gamma(z,u) \equiv \int_0^u x^{z-1} \exp(-x)\, dx$ denotes the incomplete Gamma function.

For claimants, it follows by plugging into (3.10) and replacing theoretical by estimated values that

$$\frac{[-\ln(1-p_i)]^{1/\theta_1} - \gamma(1/\theta_1+1,-\ln(1-\ell_i))/p_i}{\left[-\frac{dp_i}{dS_i}\frac{1}{v_S}\right]\frac{1}{\theta_1}[-\ln(1-p_i)]^{(1-\theta_1)/\theta_1}\frac{1}{1-p_i} + \left[-\frac{dh_{IT-1}}{dE_i}\frac{1}{Bv_E}\right]\beta^{-1}\frac{a_{0i}}{\theta_{0i}}a_1(a_1-1)h_{IT-1}^{a_1-2}}$$
$$\leq \Delta A \leq \frac{[-\ln(1-p_i)]^{1/\theta_1} - \gamma(1/\theta_1+1,-\ln(1-\ell_i))/p_i}{\left[-\frac{dp_i}{dS_i}\frac{1}{v_S}\right]\frac{1}{\theta_1}[-\ln(1-p_i)]^{(1-\theta_1)/\theta_1}\frac{1}{1-p_i}},$$

while for the non-claimants, using 3.11), it follows that

$$\frac{[-\ln(1-p_i)]^{1/\theta_1} - [\Gamma(1/\theta_1+1) - \gamma(1/\theta_1+1,-\ln(1-\ell_i))]/(1-p_i)}{\left[-\frac{dp_i}{dS_i}\frac{1}{v_S}\right]\frac{1}{\theta_1}[-\ln(1-p_i)]^{(1-\theta_1)/\theta_1}\frac{1}{1-p_i}} \leq \Delta A \leq$$
$$\frac{[-\ln(1-p_i)]^{1/\theta_1} - [\Gamma(1/\theta_1+1) - \gamma(1/\theta_1+1,-\ln(1-\ell_i))]/(1-p_i)}{\left[-\frac{dp_i}{dS_i}\frac{1}{v_S}\right]\frac{1}{\theta_1}[-\ln(1-p_i)]^{(1-\theta_1)/\theta_1}\frac{1}{1-p_i} + \left[-\frac{dh_{IT-1}}{dE_i}\frac{1}{Bv_E}\right]\beta^{-1}\frac{a_{0i}}{\theta_{0i}}a_1(a_1-1)h_{IT-1}^{a_1-2}}.$$

4 | Job Mobility and Creative Destruction: Flexicurity in the Land of Schumpeter

Joint with Francis Kramarz and Josef Zweimüller

A version of this paper has been submitted to *Econometrica*.

4.1 Introduction

Lack of labor market flexibility resulting from, among other things, high firing costs is considered to be one of the most important factors driving the high unemployment rates and low productivity in some Southern European countries. Such costs tend to discourage workers from searching for better job matches; and it forces firms to continue inefficient employment relationships, resulting in sub-optimally low productivity and low output. Moreover, as workers are reluctant to move firms have fewer incentives to create new jobs, either because they anticipate low arrival rates by currently employed workers or high adjustment costs if employment has to be reduced. Nevertheless, while this narrative belongs to the standard repertoire when describing especially (Southern) European labor markets, there is little empirical evidence trying to establish a causal link between firing costs and worker mobility.

To shed light on this issue, this paper looks at a major change in Austrian labor market regulations: the introduction of an occupational pension scheme for private sector workers and the simultaneous abolition of a previous system of severance pay. The new system was implemented for all employment relationships starting after January 1, 2003, whereas jobs that started before this date continued to be subject to the old system. Thus, a comparison of jobs starting before the date of the policy change with jobs starting after this date is informative on how workers and firms react to the introduction of occupational pensions and the simultaneous abolition of severance pay.

The switch from the old Austrian severance pay system to the new occupational pension system brought about two major changes. The first change concerns eligibility rules with respect to quits and layoffs. Under the old severance pay system, only layoffs were subject to severance pay, whereas (voluntary) quits were not eligible. Under the new occupational pension system, both (voluntary) quits and (involuntarily) laid-off workers keep their accumulated separation payments on the pension account (and transfer it to a new employer once they have a new job). The second major change involved a switch from from a discontinuous schedule to a continuous scheme. Under the old severance pay system, job losers with less than 3 years of tenure were not eligible for severance pay; and severance pay amounted to 2 (3, 4, 6, 9, 12) monthly wages when the worker had at least 3 (5, 10, 15, 20, 25) years of tenure. The introduction of occupational pension accounts made this schedule for separation payments continuous (with monthly employer contributions of 1.53 % of the worker's salary) with workers keeping them upon job separation (the account being transferred to a new employer when a new job is started).

This paper studies how this policy change from severance pay to occupational pensions affects job mobility. Notice that the policy change affects the incentives of workers who anticipate a major shock to their firm and a high likelihood of being laid off. Under the old severance pay system, workers have an incentive to "wait for a layoff" (as a layoff is associated with a severance payment) but a low incentive to quit (as quitting is associated with the loss of the severance payment). Hence job mobility under the new system of occupational pensions should be higher than under the old severance pay system.

To identify the impact of the policy change on job mobility, we look at job separations before a mass layoff. An important literature (Jacobson, LaLonde, and Sullivan (1993);Fallick (1996);Stevens (1997)) has documented that a job loss has long-lasting effects on a worker's future career. This literature also emphasizes the importance to account for worker mobility immediately before a mass layoff (Pfann and Hamermesh (2001) among others). Our empirical approach builds on this literature and identifies the impact of the switch from severance pay to occupational pensions focusing on worker mobility preceding a mass layoff.

We are able to isolate the reform's effect on worker mobility from confounding factors such as the firms' reaction to the workforce composition as well as the business cycle using a regression discontinuity (RD) approach. In particular, we compare workers starting a job shortly after the reform to those starting shortly before. Since the economic environment as well as the workforce composition of the typical firm employing them has not changed, we know that any observable change has to be due to workers' reaction to the reform.

We find that the policy change had a significant impact on job mobility. Consider two workers, both employed in a firm that experiences a mass layoff two years from now.

According to our baseline estimates, the probability that a worker subject to the new system is still employed at the firm at the date of the mass layoff is 12.5 percentage points (or around 40 percent relative to the pre-reform mean) lower than the corresponding probability of a worker subject to the old system. Looking more closely into the effect, we find that most of the reaction is driven by the workers' higher propensity to move directly to other jobs as opposed to transitions into unemployment. This is consistent with the reform incentives as the workers subject to the new system have higher incentives to search on the job in order to decrease the risk of becoming unemployed and to move to better paying jobs.

We also demonstrate that the finding is robust to various variations of the baseline setting. On the one hand, we probe the exact definition of an adverse shock to the firm in various ways and find no effect. On the other hand, we define a sample of "matched control" workers that are comparable in observable characteristics to the baseline sample at the time of the job start, but do *not*Êhappen to enter a firm about to experience a mass layoff. We show that this sample evolves smoothly around the reform cutoff, which makes it appear unlikely that other unobserved factors drive our findings. Moreover, while there is no direct test of selection around the discontinuity, we demonstrate that workers appear to be "as good as randomly assigned" around the cutoff by finding no significant discontinuity in observable characteristics and no bunching in the number of job starts.

In order to put our quantitative results into perspective and to draw broader conclusions by exploring the reform's aggregate implications, we propose an equilibrium search model featuring endogenous layoffs and job-to-job mobility. In a new match, workers start out as non-eligible for severance pay and then turn eligible with some probability. Firms face productivity (or demand) shocks, changing the likelihood that a worker in a distressed firm will experience a layoff. When the layoff probability is high, a worker who might lose a severance payment will wait for being laid off under the old system (rather than searching hard for a new job and accepting reasonable job offers), while a worker who will keep the payment (because the separation payment can be transferred to a new employer) will be more likely to move and accept a new and more efficient employment relationship. We estimate the model by Simulated Method of Moments to find the parameter values that are most in line with the data. It turns out that, under realistic parameter values, the estimated model generates differences in mobility behavior of a similar order of magnitude as those found in the empirical analysis.

The model also predicts (comparing steady states) a moderate decrease in the equilibrium unemployment rate by around 0.6 percentage points, which is mainly driven by higher job creation. Along with this goes a mild productivity increase (output per worker increases by around 0.33 percentage points) which is driven by reallocation: Workers move more quickly to more productive jobs, which shifts the stationary productivity distribution to the right.

In a last step, we use the parameterized model to conduct policy simulations in order to explore potential effects of a comparable reform in other economies. In particular, we first argue that the Austrian pre-reform system was mild in comparison to the system currently in place in many Southern European countries, where workers become eligible for severance pay much more quickly and the expected size of the payment is much higher (with the additional risk of potential litigation). If we calibrate the model to match these facts, we predict considerable reform effects, with unemployment dropping by almost 5 percentage points and productivity increasing by around 0.66 percentage points (leading to an increase in output by over 6 percentage points). Moreover, in order to account for an important stylized fact in these economies, we propose a variant of the baseline model where we allow for temporary jobs. We estimate the model on Austrian data and again conduct policy simulations. We now find that the reform impacts both margins alike, with the share of temporary employment and unemployment each dropping by over 3 percentage points.

The paper is organized as follows. The next section reviews the related literature. Section 4.3 gives an overview of the institutional setting before and after the reform. Section 4.4 describes our data and the empirical strategy. In Section 4.5, we present empirical evidence on worker mobility in declining firms. Section 4.6 describes the specification of our model. The estimation strategy and identification is explained in Section 4.7, while Section 4.8 discusses the results and model fit. In Section 4.9, we conduct policy simulations and Section 4.10 concludes.

4.2 Related Literature

The theoretical literature on severance pay was sparked by Bentolila and Bertola (1990) and Bertola (1990). As demonstrated by Lazear (1990), in a frictionless environment any severance payment scheme can be offset by an efficient labor contract and thus should not have real effects. As a response, subsequent theoretical work analyzing the effects of lay-off costs introduced frictions of different forms, such as indivisible labor (H. Hopenhayn and Rogerson (1993)), or search frictions (e.g. Burda (1992); Saint-Paul (1995); Alvarez and Veracierto (1998); Garibaldi (1998); Cahuc and Zylberberg (1999); D. T. Mortensen and Pissarides (1999)). As discussed in Ljungqvist (2002), these models produced mixed results on the effect of lay-off costs on overall employment level.

In addition to this literature, normative theories have emerged (see Parsons (2013) for a recent overview), arguing that severance packages arise as optimal contracts in certain market environments. A recent example is Boeri, Garibaldi, and Moen (2013), who show that tenure-related severance pay is optimal if there are wage deferrals and moral hazard on the side of employers and workers.

A more recent strand of literature stresses the importance of on-the-job search and voluntary payments (see, e.g., Fella (2007) and Postel-Vinay and Turon (2014)). In particular, employers hit by an adverse shock may find it worthwhile to make a transfer in order to induce a worker to accept an outside offer.

On the empirical side, there is a number of studies using cross-country variations that find that higher employment protection reduces job or labor turnover (e.g. Gomez-Salvador, Messina, and Vallanti (2004); Micco and Pagés (2006); Messina and Vallanti (2007); Haltiwanger, Scarpetta, and Schweiger (2008)), while Gielen and Tatsiramos (2012) show that quits respond less to reported job satisfaction in countries with higher job protection. Other studies use within-country variation (e.g. Boeri and Jimeno (2005); Autor, Donohue, and Schwab (2006); Kugler and Pica (2008); Fraisse, Kramarz, and Prost (2014)) and generally find a negative effect on job or labor turnover, while yielding ambiguous results in terms of employment. Our empirical strategy relies on the behavior of workers in distressed firms (firms with mass layoffs or plant closures). On this last side, a large literature has used plant closures or mass layoffs to study how job losses affect the long-run career prospects of such workers and has typically found large and long-lasting effects. For recent studies, see e.g. Huttunen, Moen, and Salvanes (2011), Song and von Wachter (2014), Schmieder, von Wachter, and Bender (2010), Ichino, Schwerdt, Winter-Ebmer, and Zweimüller (2014), among many others.

4.3 Institutional Background

Before the 2003 reform introduced the occupational pension system, a system of mandatory severance pay was in place. All jobs that started before January 1, 2003 were subject to the old severance-pay system, while all jobs that started on January 1, 2003 or later became subject to the new occupational-pension system[1].

[1]This implies that jobs that started before 2003 and are still ongoing after January 1, 2003 continue to be covered by the old severance-pay system. However, the 2003 reform also allowed for the possibility to convert these old-system contracts into new-system contracts, provided that both employee and employer agreed to the switch. There were two possibilities to switch. (i) The *partial switch* "freezes" the severance pay at the level for which the employee is currently eligible and starts the occupational pension account at that date. When the employee quits, she can only transfer the pension to the new employer but loses the "frozen" severance pay. (ii) The *full switch* pays the severance pay to which the employee is currently eligible into a new pensions account. Notice that only for full switchers the incentive to wait completely disappears, while it does not (fully) disappear for partial switchers.

When interpreting our empirical results below, we consider a worker to be eligible for the old-severance pay rules if her job started before January 1, 2003. Similarly, we consider a worker as eligible for the new

The old severance-pay system. The pre-reform system requires firms to make a lump-sum transfer to each laid-off worker. The size of this transfer depends on the worker's tenure and is increasing in steps: After 3 years of tenure, workers become eligible for severance pay of at least 2 monthly salaries, while there is no mandatory payment below this tenure level. After 5, 10, 15, 20, 25 years of tenure, the severance pay increases to at least 3, 4, 6, 9, 12 monthly salaries, respectively. Importantly, the worker is eligible only after an involuntary layoff, while quits and dismissals for cause are exempt from the severance-pay rule. This means firms have to make a transfer in case of a layoff, a job termination upon mutual agreement (of firm and worker), or after the end of a temporary contract. However, in case of a worker-induced job termination (quit or dismissal for cause), the worker is not eligible. The only exception are quits for retirement. In that case, the firm has to provide a severance payment given the worker has at least 10 years of tenure[2].

The new occupational-pension system. All jobs starting as of January 1, 2003, (new-system) are subject to the new system of occupational pensions. Starting from the second month of the employment relationship, the employer has to transfer 1.53 percent of the worker's current salary to a pension account, on which the employee earns interest. When the job is terminated—be it through a layoff or a quit—the worker continues to be the owner of the pension account. While the claims are never lost, accessing the pension account is regulated. Withdrawing funds is only possible after three years of tenure; after a layoff; when firm and worker mutually agree to terminate the employment contract; and after the end of a temporary contract. When the worker quits (or is dismissed for misconduct), no right to withdraw from the pension account exists.

Changes in incentives as a result of the reform. The 2003 reform relates to severance-pay eligibility after a voluntary quit. Under the old system, severance-pay claims are lost. Under the new system, the worker continues to own the accumulated

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occupational-pension rules if her job started on January 1, 2003 or later. In the data, we can only observe the start date of a new job but not the type of contract (and whether an old contract was converted to a new one). This implies we may erroneously classify workers who started their jobs before 2003 as subject to the old system if in fact their contracts were converted to the new system. No such ambiguity exists for workers who started their jobs in 2003 or later (it was no option to convert a new contract to pre-reform rules). Notice that the resulting measurement error in the treatment status will bias the estimated reform effect towards zero, which means we will estimate a lower bound of the true reform effect. In practice, only a negligible number of contracts under the old system were converted to the new system (see, e.g., Percher (2003)). For this reason, any bias of the estimated reform effect will be small.

[2]See Manoli and Weber (2016) who study how severance pay rules affect retirement behavior of Austrian workers. They find that transitions to retirement are significantly lower (higher), immediately before (after) a tenure threshold, suggesting that workers align the timing of retirement to the severance pay rules.

funds on the pension account. As a result, the *incentive to wait for a layoff* (and the associated severance payment) is strong under the old system and disappears under the new system. By contrast, we should expect new-system workers employed by firms experiencing adverse shocks to search more actively on the job to limit the risk of becoming unemployed and to benefit from wage increases. In the empirical part below, we show that the abolition of severance-pay indeed lead to higher job separations among workers with high layoff probabilities. We also show that the higher probability of a job separation is largely driven by an increase in job-to-job mobility. This supports the claim that under the system workers are more willing to accept outside offers.

In contrast, the reform did not create first-order changes in firms' incentive to terminate an employment relationship (though it might have affected firm incentives through general equilibrium effects). The reason is that the reform was designed to be roughly cost-neutral (in expected value) for employers. The old system mandates substantially higher severance-pay claims than the funds accumulated on the pension account under the new system when comparing equal tenure levels (larger than 3 years). This compensates for the fact that firms in the old system firms had to make the transfer only in case of a layoff and tenure above 3 years, while in the new system firms have to make payments to all workers, irrespective of the cause of a job termination and the tenure level.

Apart from the incentive to wait for a layoff, a second main part of the severance-pay reform also removed the *incentive to wait for retirement*. Under the old system, workers with more than 10 years of tenure remained eligible for the severance payment, even if they quit voluntarily, provided that they completely withdraw from the labor force and claim a public pension thereafter. This implies that a long-tenured worker had an incentive to abstain from quitting even when her layoff probability in the current firm was very low. Staying with the firm until retirement ensured the severance payment.

In this paper we will mainly focus on the incentive to wait for a layoff and we will show that, empirically, this is the important margin where the severance-pay reform triggered substantial mobility responses. However, we will also shed some light on the impact of the reform on job mobility for longer-tenured workers who are close to retirement. While the severance pay reform created a substantial change in incentives, this did not lead to major mobility responses because job mobility in the concerned age groups is low anyway.[3]

[3] A further change of the 2003 reform was the switch from a severance-pay schedule firm that changed *discontinuously* with tenure on the current job to an occupational pension scheme where any tenure discontinuity disappears (because firms pay pensions contributions month by month into the worker's pension account). Other papers have shown that the tenure discontinuities of the old system affected unemployment durations (Card et al. (2007)) and the timing of retirement (Manoli and Weber (2016)).

4.4 Data and Empirical Strategy

Data sources. Our analysis is based on the Austrian Social Security Database (ASSD), which covers the universe of Austrian private sector workers and provides longitudinal information on the workers' earnings- and employment history from 1972 onward. The data has been collected in order to verify old-age pension claims and hence covers all information relevant to calculate a worker's pension benefit. In addition to individuals' earnings- and employment history, the ASSD reports other labor market states, such as registered unemployment, sickness or maternal leave.

We also make selective use of the Austrian Earnings-Tax Database (ATD), which covers the universe of private sector earnings-tax records and can be matched to ASSD via an individual identifier for the years 1994 to 2012. It is based on reports the employer has to complete for the tax office every year. The report contains the base salary and several other categories. In general, employees are not obliged to file individual tax returns, since the reports by the employer are detailed enough. Among other things, tax reports also report income subject to the fixed tax rate of 6%, among which is also a category for severance payments. This category comprises three types of payment: (i) mandatory severance-pay, (ii) voluntary severance-pay, and (iii) refunds for vacation days not taken.

Baseline sample. To test whether workers respond to the severance-pay reform we focus on workers who are likely to be displaced in the future. In this group of workers, the old system generates an incentive to wait, while no such incentive exists in the new system.

More precisely, we look at workers who entered a firm that subsequently experienced a mass layoff. The idea is that these workers can reasonably expect to be laid off in the near future. In the old system, these workers had an incentive to wait for the layoff in order to collect the severance payment. In the new system, this incentive is gone. Job separation outcomes in this group of workers should thus be informative about the effect of the severance pay reform on job mobility.[4]

Column 1 of Table 4.1 reports descriptive statistics for all job starters observed in the ASSD who satisfy the following criteria: (i) aged 25-55 at job start, (ii) started a new job during the period January 1, 1997 to December 31, 2008, (iii) stayed at least

[4] If a worker is employed in a secure job (with a layoff probability equal to zero), the severance pay reform does not generate any differential incentives in terms job mobility. In the old system, the worker gets the severance payment as a lump-sum at retirement, while in the new system the firm pays continuously into the worker's pension account that the worker can take with her to the new employer. As the expected transfers under both systems are equally large, incentives to switch job remain unchanged after the reform for workers with a zero layoff probability.

12 months in the new firm. Column 3 restricts attention to the subsample of workers who entered a firm that subsequently experienced a mass layoff. To be selected into our baseline sample, the worker must have (iv) entered a firm, which experienced a mass layoff 3 to 4 years later. A "mass-layoff" firm has to satisfy the following characteristics: (a) an employment reduction of more than 33 percent of the firm's work force; (b) the employment reduction has to occur within one month; and (c) the firm had at least 30 employees in the last month before the mass layoff. Workers who satisfy criteria (i) - (iv) constitute our "baseline sample".

Table 4.1: Summary statistics, all job starters and baseline sample

	All Job Starts	Reweighted	Baseline
Female	0.55	0.53	0.51
Age (years)	37.79	37.59	36.73
Experience (years)	13.13	13.14	11.79
Austrian	0.79	0.79	0.78
Previous Jobs	4.99	4.97	5.37
Manufacturing	0.22	0.25	0.24
Vienna	0.32	0.33	0.36
Starting wage in €	1,779	1,876	1,992
Number of Firms	173,528	173,528	4,198
Median firm size at entry	98	210	212
Median firm size before shock	.	.	222
Median size reduction	.	.	175
Observations	1,300,062	1,300,062	28,099

Note: Column 1 of the table reports descriptive statistics for the universe of newly hired workers observed in the ASSD who satisfy the following criteria: (i) aged 25-55 at job start; (ii) started a new job between January 1, 1997 and December 31, 2008; (iii) stayed at least 12 months in the new firm. Column 3 restricts attention to the subsample of workers who (iv) entered a firm that experienced a mass layoff within 3 to 4 years after the worker's job start date. Workers who satisfy criteria (i)-(iv) constitute our "baseline sample". Column 2 is based on workers satisfying criteria (i)-(iii), but reweights observations according to the firm size distribution observed in the baseline sample at the time of the job start, which differs by construction as we restrict to firms with at least 30 employees before the mass layoff. We group observation in 50 size quantiles, hence the median firm size does not necessarily correspond to the baseline sample exactly. The table shows that the baseline sample of mass layoff workers shows by and large similar characteristics, though starting wages are somewhat higher in the baseline sample. Reweighting shows that part of this discrepancy is explained by differences in firm size.

Table 4.1 compares the characteristics of workers in our baseline sample to all prime-age job starters (irrespective of whether the firm subsequently experienced a mass layoff), showing that workers in the baseline sample are slightly less likely to be female, younger, and more experienced. Due to criteria (iv) and (v) baseline workers are (mechanically) selected from larger firms and have higher wages. Overall, the baseline sample of mass layoff workers shows by and large similar characteristics, though starting wages are somewhat higher in the baseline sample. (In column 2, we reweight observations in the universe to match the average firm size of the baseline sample which reduces the difference in average wages.) The median employment reduction during the subsequent mass in the baseline sample is 175. The median size of a firm is 212 in the month of entry and 222 one month before the mass layoff. Hence, on average, employment levels even slightly increased up until the month immediately before the mass layoff.

Empirical strategy: RD design. To identify the effect of the severance-pay reform on job mobility, we exploit the fact that the policy changed discontinuously on January 1, 2003. In our baseline specifications we will estimate local linear regressions of the form

$$Y = \beta_0 + \beta_1 D + \beta_2 x + \beta_3 D \times x + \varepsilon, \tag{4.1}$$

where Y denotes the outcome variable, which is in our case an indicator for job mobility—a separation from the current job (in the mass-layoff firm) which can either be a transition to a new job, a transition to unemployment, or a transition to non-employment—D is a dummy variable that indicates whether the job started on January 1, 2003 or later (so that the employment contract is subject to the new occupational pension system) worker, x denotes the start date of the job (normalized to take the value 0 at the time of the reform) and ε captures unobservables.

The main identification assumption is that heterogeneity in the absence of the treatment evolves smoothly around the threshold, so that workers arbitrarily close to the cutoff are "as good as" randomly assigned. In this case β_1, the parameter of interest, measures the reform impact.

We restrict all analyses to an RD sample of at most 24 quarters around the cutoff but explore the robustness to smaller bandwidths. We put more weight on observations close to the cutoff by using a triangular kernel following the suggestions by Porter (2003) and Hahn et al. (2001). Standard errors are computed using a bootstrap (1000 replications) clustered at the firm level to account for potential correlation in unobservables at the firm level.

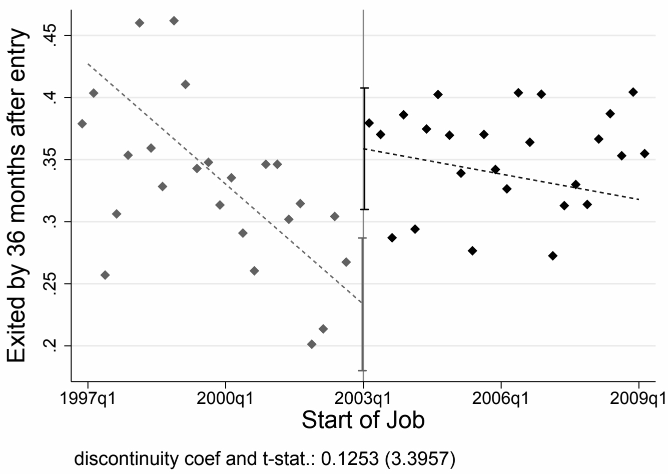
4.5 Job Mobility and the Severance-Pay Reform

In what follows we present empirical estimates on the 2003 severance pay reform's causal effect on job mobility. Our empirical strategy relies on a regression discontinuity design (RDD) which treats the start date of a new job as the running variable and the date of implementation of the severance-pay reform, January 1, 2003, as the critical threshold.

We first provide our main results which document an upward jump in job mobility immediately after the reform was implemented. We then provide a detailed check of the validity of our RDD and perform a number of robustness checks that document that our main results are quite robust. Finally, we look at further outcomes, such as wage increases for job changes and job mobility for long-tenured workers (whose job mobility might have increased because the reform removed the incentive to wait for retirement).

Main results. Figure 4.1 documents a discontinuous increase in the fraction of job separations in response to the reform. On the vertical axis we measure the percentage job separations that took place *before* the mass layoff. Recall that the baseline sample includes workers who stayed for at least 12 months and who were hired by a firm that experienced a mass layoff 36 to 47 months after the worker's job start. The vertical axis measures the percentage of job separations, which we define as the fraction of workers having left the firm before reaching 36 months of tenure.[5] The horizontal axis refers to the quarter during which workers in the sample were hired by a firm that subsequently experienced a mass layoff. The vertical line in the middle of the graph indicates the reform date: jobs that started before this date are still subject to the old severance-pay system; jobs that started after this date are subject to the new occupational-pension system.

Figure 4.1: Job separations by date of job start



Note: The figure plots the fraction of workers in our baseline sample ($N = 28,099$)—among those who have entered a firm at the date specified on the horizontal axis, "Start of job"—who stayed in this firm less than 36 months, conditioning on a tenure of at least 12 months. The red vertical line displays the date of the severance-pay reform (2003q1). Jobs that started after (before) the reform date were subject to the new (old) system. The fitted lines and confidence intervals are from a local linear regression with triangular weights. Inference is based on a bootstrap (1000 replications), clustered at the firm level. The figure displays a stark discontinuity at the reform date: jobs which started immediately after the reform are significantly more likely to be terminated than jobs which started immediately before the reform date. This is in line with the incentive to wait for a layoff in the old system, which disappeared after the reform. (See text for details.)

The graph indicates a clear discontinuity at the reform date: among workers who started their job immediately before the reform date, below 25 percent have left the firm

[5]In the robustness checks below we look at alternative definitions of the job separation measure. Our main results are based on a fixed time window for job separations (percentage leavers within 36 months after job start). Alternatively, we define a separation indicator based on a variable time window for job separations (percentage leavers by 1 month before the mass layoff). The former indicator keeps the separation time window fixed but is subject to a variable time to the mass layoff. The latter indicator keeps the time to the mass layoff fixed but is subject to a variable time since job start. Our RDD estimates are robust to this change of definition in the job separation indicator.

before reaching 36 months of tenure. The corresponding number jumps up to above 35 percent for workers who started their job immediately after the reform date. This indicates that the 2003 reform had a large and statistically significant impact. Job separations increased by 12.5 percentage points or by 40 percent relative to the pre-reform mean.

Figure 4.2 distinguishes job separations by transitions to a new job (panel (a)) and transition to unemployment (panel (b)), coding a transition as job-to-job (JTJ) if intermittent nonemployment is below 28 days, while calling all other transitions job-to-unemployment (JTU). Panel (a) shows a significant and quantitatively large discontinuity in JTJ transitions, while panel (b) indicates that also transitions to unemployment (JTU) are affected, though the discontinuity is smaller and only weakly significant. JTJ transitions increase from less than 9 percent immediately before to above 15 percent immediately after the reform, suggesting that JTJ transitions increased by more than 60 percent in response to the reform. In contrast, JTU transitions increase from 13 to 17 percent, corresponding to roughly 30 percent.

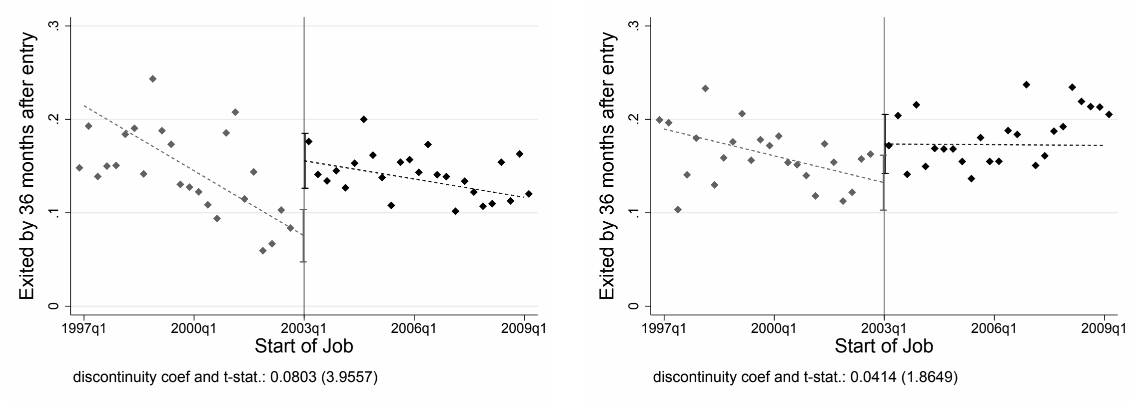
As a first-order approximation, it is reasonable to assume that transitions to new jobs predominantly reflect voluntary quits, while transitions to unemployment are more likely driven by involuntary job terminations. To the extent that this approximation is correct, our results indicate that the increase in job separations caused by the 2003 reform is mainly due to workers' higher willingness to move to new jobs. This is in line with reform incentives. Notice that assuming that only JTJ moves are responses to the reform in line with incentives may underestimate the true response. We might erroneously classify a transition to unemployment as "involuntary" when the worker already found a new job but decides to stay on UI benefits for an intermediate period. (An error in the opposite direction is less likely because a transition to a new job after an involuntary layoff can only happen when a fired workers finds a new job immediately.) We conclude that worker-induced transitions to a new job is likely to underestimate the reform's effect on job mobility.

Table 4.2 summarizes the results in a series of RDD regressions. The table reports the RD-coefficient from various linear probability models based on specification (4.1). Columns 1 to 3 use the entire sample, while columns 4 and 5 use the optimal bandwidth according to Imbens and Kalyanaraman (2012). Columns 3 and 5 include covariates, while column 3 uses a quadratic specification to capture potential nonlinear effects of the running variable (calendar time).

Regression results are robust and confirm the graphical evidence of Figures 4.1 and 4.2 above. Panel A uses all job separations as the outcome variable and estimates that the severance-pay reform increases job separations by 11 to 14 percentage points in our baseline sample. As a fraction of the pre-reform mean, this amounts to a 40 percent

Figure 4.2: Transitions to a new job (JTJ) vs unemployment (JTU), by date of job start

(a) Transitions to a new job (JTJ) (b) Transitions to unemployment (JTU)



Note: Panel (a) plots the fraction of workers in our baseline sample ($N = 28,099$) by job start date, who transitioned to another job (JTJ) between month 12 and month 36 after their job start date, conditioning on a tenure of at least 12 months. Panel (b) plots the corresponding fraction of workers who entered unemployment (JTU) between month 12 and month 36. The fitted lines and confidence intervals are from a local linear regression with triangular weights. The vertical line indicates the reform date. Inference is based on a bootstrap (1000 replications), clustered at the firm level. In line with reform incentives, the fraction of JTJ movers shows a discontinuous and sizable upward jump for jobs that started immediately after the reform. The fraction of JTU movers also displays an upward jump, but the effect is considerably smaller and barely statistically significant. (See text for details.)

increase in job separations. Panels B and C run the same RD models using, respectively, transitions to a new job and to unemployment as outcome variables. JTJ transitions increase by 7 to 10 percentage points, or by 54 to 85 percent in terms of the pre-reform mean. The reform effect on JTU transitions is also positive, but substantially smaller in absolute (and relative) value and less precisely estimated.

The results of Figures 4.1 and 4.2 and Table 4.2 define as outcome an indicator for a job transition, which took place 12 to 36 months after the workers was hired. To see how the effect builds up, we look more specifically into the timing of these additional job transitions. Denote by $y_{12,x}$ an indicator that takes value 1 if a transition occurs between month 12 and month $x > 12$ (among workers with tenure ≥ 12 months). Instead of only using $x = 36$, we ran 12 regressions using $y_{12,x}$ as outcome with $x = 14, 16, \ldots, 36$. Figure 4.3 reports the 12 RD coefficients when the outcome variable is based on all job-separations (panel a), JTJ transitions (panel b), and JTU transitions (panel c), respectively.

The graphs clearly show that the effect builds up smoothly. The increase in job separations is paralleled by an increase in JTJ transitions, while JTU transitions do not increase that much with tenure after month 20. The figures indicate that the increase in job separations at dates closer to the mass layoff is almost entirely driven by increases in JTJ transitions. This is further support for the claim that the reform has mainly affected workers' willingness to quit and move to new jobs.

Table 4.2: Dependent variable: probability of separation by 36 months after entry

	(1)	(2)	(3)	(4)	(5)
Panel A: All exits					
Estimated coefficient	0.125***	0.136***	0.111***	0.128***	0.130***
	(0.0371)	(0.0468)	(0.0294)	(0.0454)	(0.0387)
Pre-reform mean	0.316	0.316	0.316	0.280	0.280
Effect relative to pre-reform mean	0.396	0.431	0.350	0.457	0.466
Panel B: Job-to-Job					
Estimated coefficient	0.0803***	0.0870***	0.0729***	0.0992***	0.0996***
	(0.0200)	(0.0247)	(0.0186)	(0.0270)	(0.0242)
Pre-reform mean	0.135	0.135	0.135	0.112	0.112
Effect relative to pre-reform mean	0.593	0.642	0.539	0.882	0.886
Panel C: Job-to-Unemployment					
Estimated coefficient	0.0414*	0.0603**	0.0372**	0.0418	0.0479*
	(0.0220)	(0.0275)	(0.0187)	(0.0260)	(0.0254)
Pre-reform mean	0.156	0.156	0.156	0.143	0.143
Effect relative to pre-reform mean	0.264	0.386	0.238	0.291	0.334
Specification					
Linear	Yes	Yes	Yes	Yes	Yes
Quadratic	No	Yes	No	No	No
Controls	No	No	Yes	No	Yes
Bandwidth(quarters)	24	24	24	10	10
Observations	28099	28099	28099	13543	13543

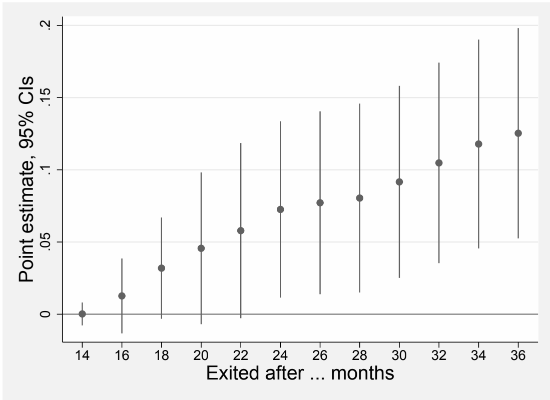
Note: The table reports the coefficient β_1 from a linear probability model based on equation (4.1). Results indicate a discontinuous increase in total job separations after the reform (panel A), which is mainly driven by JTJ transitions (panel B) and to a lesser extent by JTU transitions (panel C). The estimated effects are robust to the inclusion of control variables, the specification of the running variable and the bandwidth choice. 10 quarters is the optimal bandwidth according to Imbens and Kalyanaraman (2012). Standard errors are bootstrapped (1000 replications) and clustered at firm level. Controls are gender, age, age squared, experience, experience squared, Austrian nationality, log firm size 24 months before the mass layoff, and indicators for manufacturing sector, Vienna, and quarter of job entry; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

RDD validity. A potentially important caveat for interpreting the above RD coefficient as causal may be manipulation of the start date of the job. Note first that it is not entirely obvious whether firms (workers) have an incentive shift the start date of a planned hire forward or backward. Since the reform was cost-neutral on average, there is no clear ex-ante gain from self-selection into the old or the new system. Moreover, revealed behaviors suggest that postponing a new job to the new system was not a dominant option. Otherwise, the possibility of switching to the new system (that became possible with the reform for all ongoing employment relationships) would have been taken up much more frequently.

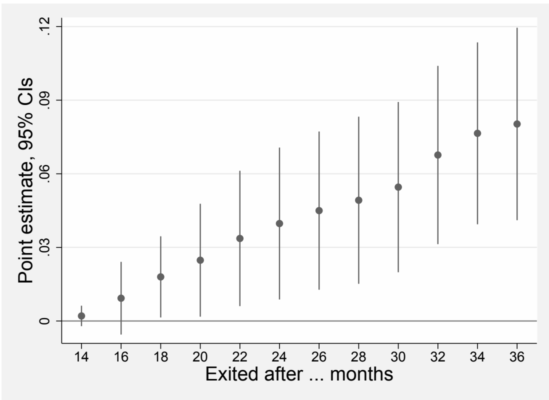
Figure 4.4 looks at the empirical evidence. The horizontal axis shows calendar year-month of job start, while the vertical axis plots the absolute number of newly hired workers by calendar year-months. Panel (a) restricts attention to our baseline sample ($N = 28,099$), Panel (b) looks at the universe of job starters ($N = 1,300,062$) observed in

Figure 4.3: How does the effect build up over time?

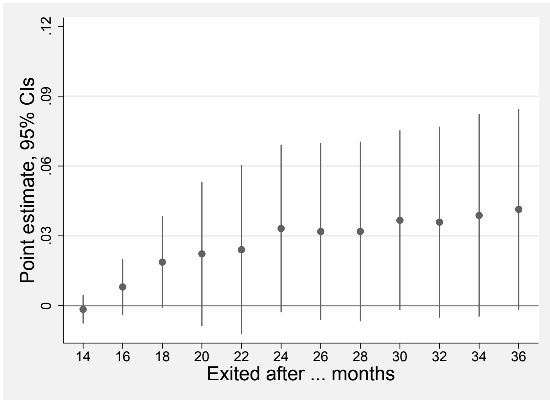
(a) All job separations



(b) Transitions to a new job (JTJ)



(c) Transitions to unemployment (JTU)



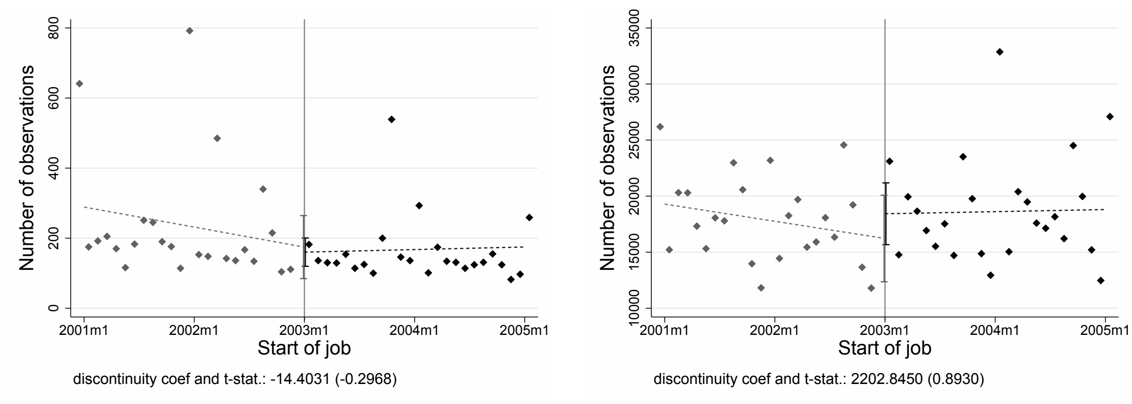
Note: The figures plot the RD coefficients β_1 estimated from equation (4.1) using our baseline sample when we vary the time window during which a job separations occurs between month 12 and month $x > 12$ after the start of a job. (This means we look at workers who stayed at least 12 months and at most $x > 12$ months in a firm that subsequently experienced a mass layoff, while in Table 4.2 we restrict attention to $x = 36$.) Panel A uses as the dependent variable an indicator for a job separation between month 12 and month x after job start; Panels B and C use an indicator for a JTJ and a JTU transition, respectively, as the dependent variable. Estimates are from a linear probability model, using the specification of column 1 in Table 4.2. Inference is based on a bootstrap (1000 replications), clustered at the firm level. Panel A shows that the fraction of separated workers increases continuously with tenure, x, panel B shows that this increase is mainly due to JTJ transitions, while panel C shows that also JTU transitions increase, but estimates are smaller and barely statistically significant. (See text for details.)

the ASSD (who satisfy the selection criteria). Figure 4.4 shows that the number of monthly hires is a quite noisy indicator. However, there is no statistically or visually significant discontinuity in the absolute number of job starts at the reform date (2003q1), neither among workers in the baseline sample, nor among all job starters. This indicates that manipulation of new hires around the reform date does not appear empirically relevant.

Figure 4.5 looks for discontinuities around the reform date in the work-force composition of firms that hired the workers in our baseline sample at different dates before the date of the mass layoff. A date point on the vertical axis takes firms that hired a

Figure 4.4: Absolute number of new hires, by date of job start

(a) Baseline sample (b) Universe



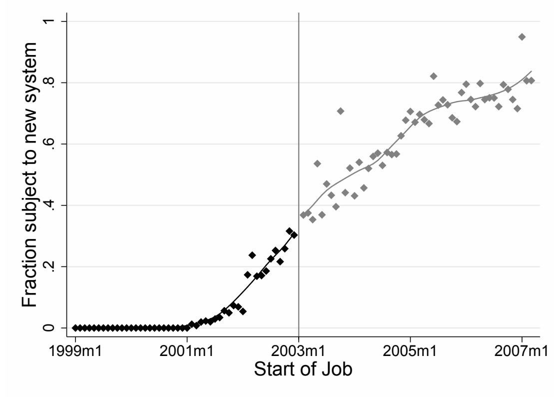
Note: The figures plot the absolute number of newly hired workers by calendar year-months. Panel A restricts attention to our baseline sample ($N = 28,099$), Panel B looks at the universe of job starters ($N = 1,300,062$) observed in the ASSD (who satisfy selection criteria). The fitted lines and confidence intervals are from a local linear regression with triangular weights. Inference is based on a bootstrap (1000 replications), clustered at the firm level. While the number of monthly hires is quite noisy, there is no statistically significant discontinuity in the number of job starts at the reform date (2003q1), neither among workers in the baseline sample, nor among all job starters. This indicates that manipulation of new hires around the reform date does not appear empirically relevant. (See text for details.)

worker of our baseline sample in the respective month and plots the mean "percentage of new-system workers". To calculate this indicator we weight by the number of baseline workers. I.e. we first assign, to each worker in our baseline sample, a (worker-specific) variable "firm's fraction of new-system workers x months before the mass layoff", where $x = 24$ months (panel (a)), $x = 12$ months (panel (b)), and $x = 1$ month (panel (c)). We then take the mean of this variable among all workers in the baseline sample who started their new job in the respective month. None of the three panels indicates a significant discontinuity around the reform date (2003m1). This suggests that a contrast of job starters immediately before and after the reform is unlikely contaminated by differences in the work-force composition of the firms that hired these new workers. Moreover, this analysis also addresses the concern that the firms' mass layoff decisions, and hence the way we select observations, might be driven by the reform. Arguably, firms having similar workforce compositions in terms of eligibility—such as the typical firms employing workers having started either in December 2002 or January 2003—should not, ceteris paribus, display systematic differences in their behavior due to the reform. Thus, we can be confident that the discontinuity is driven by worker behavior.

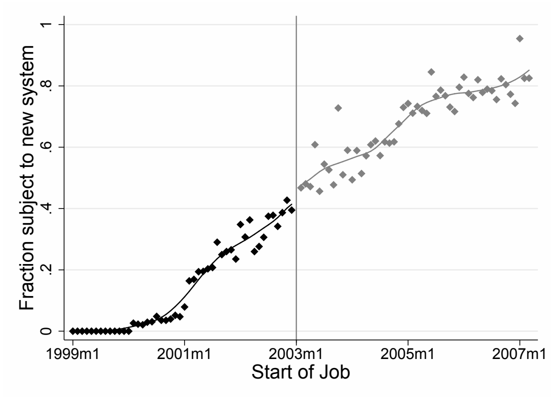
In Table 4.3 we check whether observed covariates are smooth around the threshold to detect potential signs of selection and to rule out the possibility that events or interventions other than the severance-pay reform drive the discontinuous increase in job mobility observed when the new policy was implemented. The table compares descriptive

Figure 4.5: Percentage new-system workers in total work force of the firm

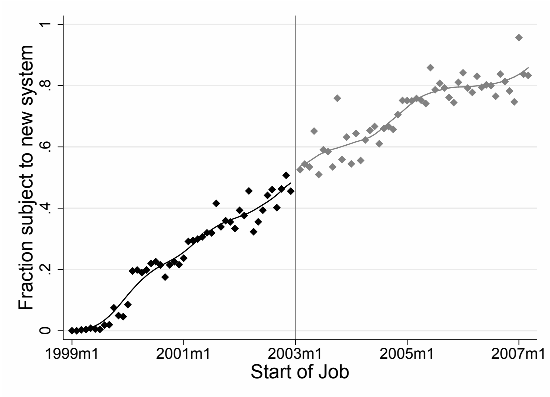
(a) 24 months before the mass layoff



(b) 12 months before the mass layoff



(c) 1 month before the mass layoff



Note: The figures look for discontinuities around the reform date in the workforce composition among the firms that hired new workers. To calculate the variable "percentage new-system workers" we first assign, to each worker in our baseline sample ($N = 28,099$), a (worker-specific) variable *"firm's fraction of new-system workers x months before the mass layoff"*, where $x = 24$ months (panel a), $x = 12$ months (panel b), and $x = 1$ month (panel c). We then take the mean of this variable among workers who started their new job in the respective month. None of the three panels indicates a significant discontinuity around the reform date (2003m1). This suggests that a contrast of job starters immediately before and after the reform is not contaminated by differences in the work-force composition of the firms that hired these new workers. (See text for details.)

statistics of the baseline sample, before and after the reform (columns 1-3), as well as the corresponding RD estimates (columns 4-5). Panel A focuses on worker characteristics, Panel B focuses on the characteristics of the firms that hired these workers. Comparing sample means does not indicate any differences before and after the policy change. Moreover, the corresponding RD estimates do not show significant discontinuities at the reform date (2003q1), neither in worker- nor in firm characteristics (the only exception being a somewhat lower percentage of females after the reform[6]).

As a next step we replicate the RD analysis, but instead of assigning the true reform

[6]Later, we will demonstrate that this small discontinuity does not affect our conclusions by showing that the effect is present even when restricting to females or males, respectively.

Table 4.3: Are covariates smooth around the cutoff?

	Mean before	Mean after	Difference	RDD estimate	p-value
Panel A: Worker characteristics					
Age (years)	36.65	36.83	0.175	-0.231	0.757
Female	0.544	0.467	-0.0776	-0.110	0.0883*
Experience (years)	11.98	11.56	-0.421	-0.452	0.715
Austrian	0.800	0.761	-0.0389	-0.0402	0.118
Log previous wage	4.024	4.159	0.135	-0.0212	0.815
Panel B: Firm characteristics					
Manufacturing	0.162	0.216	0.0545	0.145	0.157
Located in Vienna	0.314	0.426	0.112	0.129	0.260
Log firm size 2 y. bef. shock	5.668	5.445	-0.224	-0.0157	0.973
Log firm size 1 y. bef. shock	5.694	5.450	-0.243	-0.0971	0.831
Log firm size 1 m. bef. shock	5.689	5.453	-0.236	-0.116	0.794

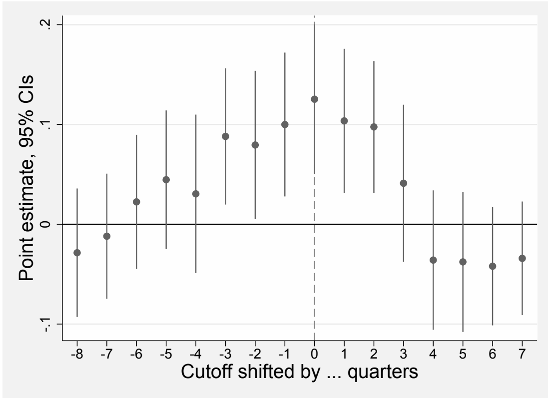
Note: The table compares descriptive statistics of the baseline sample, before and after the reform (columns 1-3), as well as the corresponding RD estimates (columns 4-5). Panel A focuses on worker characteristics, Panel B focuses on the characteristics of the firms that hired these workers. Comparing sample means does not indicate any differences before and after the policy change. Moreover, the corresponding RD estimate do not show significant discontinuities at the reform date (2003q1), neither in worker- nor in firm characteristics (the only exception being a somewhat lower percentage of females after the reform). Inference is based on a bootstrap (1000 replications), clustered at the firm level. Overall, the evidence supports the validity of the RD design. (See text for details.)

date we estimate the RD coefficients from a series of "placebo reforms". The placebo reform shifts the reform cutoff date x quarters away from the true reform date 2003q1 (the true reform date is normalized to zero), and we let x vary from 8 quarter before and 7 quarters after the true reform date. Panel (a) of Figure 4.6 uses an indicator for a job separation (12-36 months after the start of the new job) as the dependent variable; panels (b) and (c) look at, respectively, JTJ and JTU transitions during the same time interval as the outcome variable. The evidence in all three panels consistently shows that RD estimates are larger for placebo reforms closer to—and are highest at—the true reform date. This supports the idea that the discontinuous change in job separations is indeed caused by the severance-pay reform rather than by some other event or intervention.

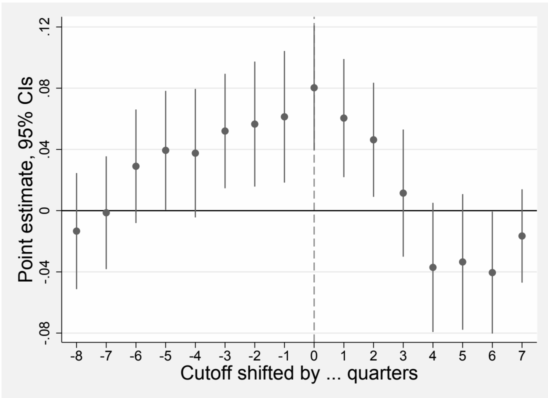
In Appendix A we conduct a number of further checks that support our RD strategy. Notice that our baseline sample is selected *as if* the mass layoff was an exogenous event. This is clearly not the case and it is important to be aware that the mass layoff is the firms' endogenous response to an exogenous shock we cannot observe. Ideally, we would like to know the exact date when the worker learns that the firm was hit by a shock and that her layoff probability has increased. We would also like to know the date when the worker is eventually informed that (and, if at all, when) she will be fired. Because these dates are unobserved, it is important to be transparent about the dynamics of mass layoff firms' employment levels before the mass layoff. In Appendix A, we provide RD contrasts of the firms which hired the workers in the baseline sample *immediately before* the severance-pay policy change, to those firms that hired baseline-sample workers

Figure 4.6: Placebo reforms

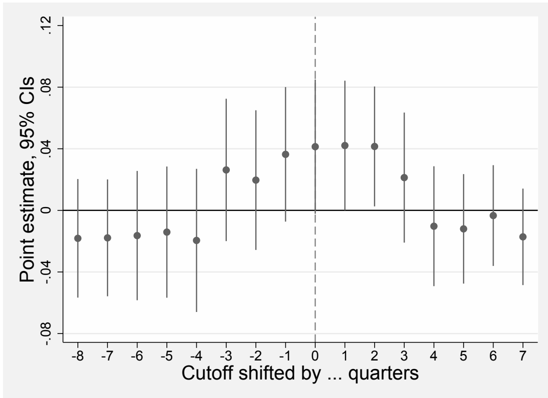
(a) All job separations



(b) Transitions to a new job (JTJ)



(c) Transitions to unemployment (JTU)



Note: The figures provide the RD coefficients from a series of "placebo reforms". The placebo reform shifts the reform cutoff date x quarters away from the true reform date 2003q1 (the true reform date is normalized to zero), and we let x vary from -8 to $+7$ quarters. Panel a) uses an indicator for a job separation (12-36 months after the start of the new job) as the dependent variable; panels b) and c) look at, respectively, JTJ and JTU transitions as the outcome variable. Inference is based on a bootstrap (1000 replications), clustered at the firm level. The evidence in all three panels consistently shows that RD estimates are larger for placebo reforms closer to – and are highest at – the true reform date. This supports the idea that the discontinuous change in job separations is indeed caused by the severance-pay reform rather than by some other event or intervention. (See text for details.)

immediately after the policy change. We document the absence of a discontinuous change at the policy threshold in the following characteristics: employment levels (at various dates before the mass layoff); absolute and relative sizes of the subsequent mass layoffs; absolute and relative employment reductions in the last two years before the mass layoff (not counting employment reduction associated with the mass layoff).

Overall, we argue that the empirical evidence supports our identification strategy. We conclude that the contrast of mobility outcomes at the policy threshold provides a valid empirical design to identify the causal effect of the severance-pay policy change on job mobility.

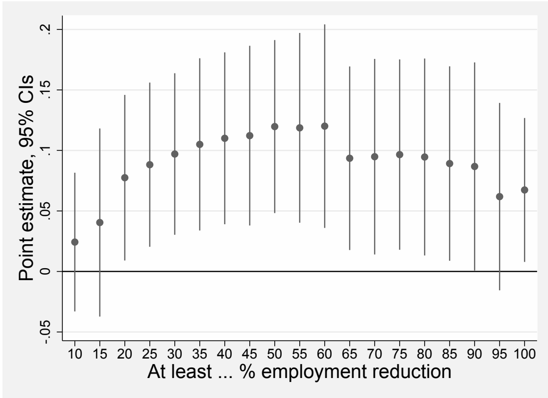
Robustness. The above main results on the effect of the severance-pay reform on job mobility are obtained from a specific sample of workers: Workers who were hired by firms which subsequently experienced a mass layoff. The definition of a mass layoff was an employment reduction of 33 percent (between months t and $t+1$), which is clearly an arbitrary number. In Figure 4.7 we check whether our main results are robust to the definition of a "mass layoff". The figures provides estimates for the RD coefficients when a mass layoff is defined as an employment reduction of x percent or more, where we let x vary from an employment reduction (between months t and $t+1$) of 10 percent to 100 percent (i.e. a plant closure). Panel (a) shows that the estimated reform effect on all separations increases in x, at least over the range $x = 10$ to $x = 60$ percent. This is in line with incentives: A higher x means a higher layoff probability for the average worker in the sample. Hence, under the old system, a higher x is associated with a stronger incentive to wait for a layoff with severance pay. In contrast, in the new system workers with an increased layoff probability will move to new jobs quickly. Panels (b) and (c) show that, indeed, the reform effect is mainly driven by higher job-to-job moves and to a smaller extent by increased transitions to unemployment. For mass layoff definitions with $x > 60$ percent, the reform effect levels off, mainly due to fewer transitions to unemployment, while the reform effect on job-to-job moves remains large.

One potentially important reason that could invalidate the RD design is that the responses of firms and workers in our baseline sample are the results of changing macroeconomic conditions or of seasonality. To explore this hypothesis we replicate our main results of Figures 4.1 and 4.2 for a sample of "matched control workers". Matched controls are hired by a firm that did *not* subsequently experience a mass layoff. The matching procedure was implemented as follows. For each worker in the baseline sample, we look for exact matches in terms of the following characteristics: hired in the same quarter and stayed on the job for at least 12 months; same gender; same region (9 "Bundeslaender"); same industry (21 categories); same age decile. If we obtain multiple controls, we take the one with the closest propensity score based on experience, experience squared, employment status in the four quarters preceding the current job, and decile of the starting wage. 4.5 percent (out of 28,099) workers in the baseline sample could not be matched and were dropped. We end up with 26,841 matched pairs.

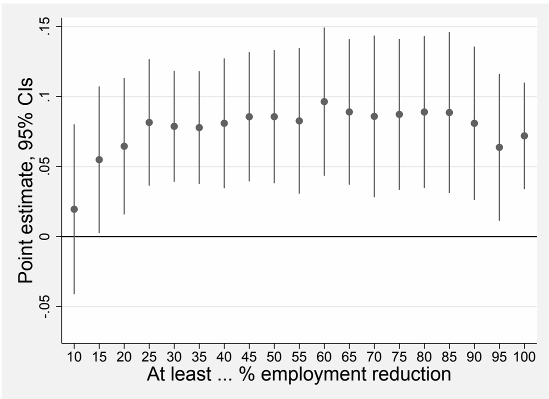
The graphs show no significant upward jump at the reform threshold. If at all, we see a slight reduction in job mobility at the date of the policy change. However, the jumps are very small and not statistically significant. We conclude that these results are in line with the incentives created by the policy change. By construction, matched control workers have a low probability of being fired and hence to do not have a strong incentive to wait for a layoff with severance pay. Hence we expect them not to be strongly affected by the

Figure 4.7: Results by alternative definitions of a mass layoff

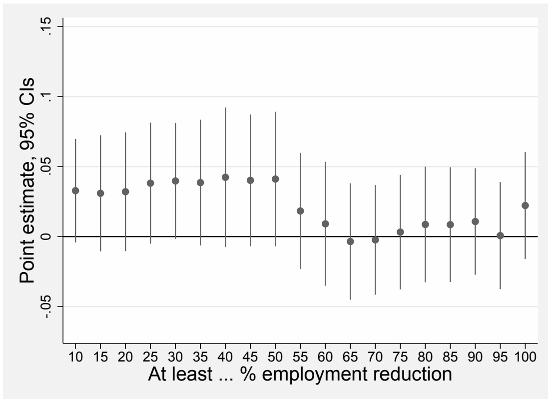
(a) All job separations



(b) Transitions to a new job (JTJ)



(c) Transitions to unemployment (JTU)



Note: The figures provides estimates for the RD coefficients when a mass layoff is defined as an employment reduction of x percent or more between months t and $t+1$. (In the baseline sample, the required employment reduction is $x = 33$ percent). Inference is based on a bootstrap (1000 replications), clustered at the firm level. Results show that the reform effect on all separations increases in x (over the range $x = 10$ to $x = 60$ percent). This is in line with incentives: A higher x means a higher layoff probability of the average worker in the sample. Hence, under the old system, a higher x is associated with a stronger incentive to wait for a layoff (with severance pay). In contrast, in the new system workers with an increased layoff probability move to new jobs quickly. Panel (b) shows that, indeed, the reform effect is mainly driven by higher job-to-job moves and to a smaller extent by increased transitions to unemployment (panel (c)). Beyond $x = 60$ percent, the reform effect levels off, mainly due to fewer transitions to unemployment, while the reform effect on job-to-job moves remains large. (See text for details.)

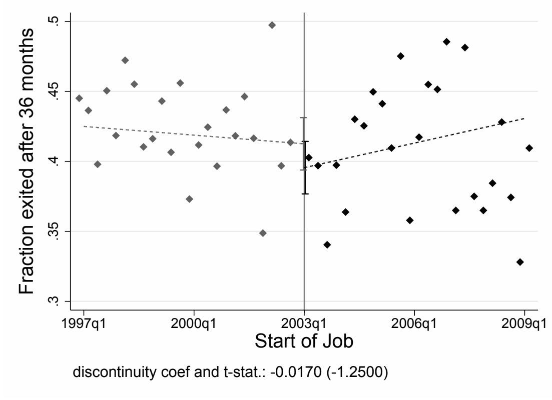
severance-pay reform.

In Table 4.4 we compare RD estimates of the reform effect on job mobility in the baseline sample (column 1) to "matched control" workers (column 2) and then conduct a diff-in-diff RD analysis (column 3). The RD diff-in-diff estimates are in line with previous results and confirm the hypothesis that the new system generates a stronger incentive to move to a new job for workers with a high firing probability (baseline sample)—but not for other workers (matched controls).

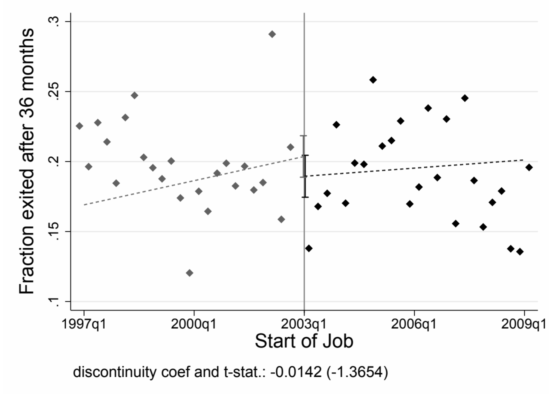
We report further robustness checks in Table 4.5, which are based on alternative

Figure 4.8: Reform effect on workers *not* in a mass-layoff firm ("matched controls")

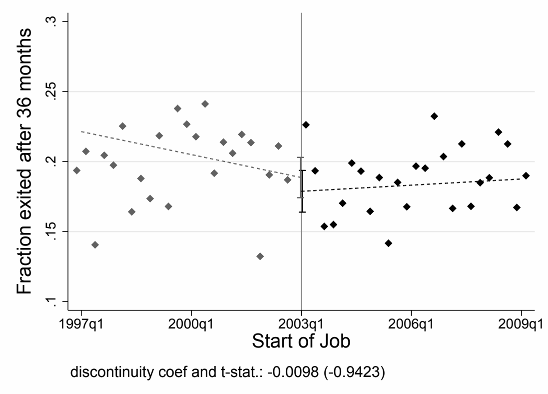
(a) All job separations



(b) Transitions to a new job (JTJ)



(c) Transitions to unemployment (JTU)



Note: The figures replicate Figures 4.1 and 4.2 for a sample of "matched control workers" hired by a firm that did *not* subsequently experience a mass layoff. For each worker in the baseline sample, we look for exact matches in terms of the following characteristics: hired in the same quarter and stayed on the job for at least 12 months; same gender; same region (9 "Bundeslaender"); same industry (21 categories); same age decile. If we obtain multiple controls, we take the one with the closest propensity score based on experience, experience squared, employment status in the four quarters preceding the current job, and decile of the starting wage. 4.5 percent (out of 28,099 workers) in the baseline sample could not be matched and were dropped. We end up with 26,841 matched pairs. Inference is based on a bootstrap (1000 replications), clustered at the firm level. The graphs confirm the hypothesis that matched control workers (who, by construction, have a low probability of being fired and hence to do not have a strong incentive to wait for a layoff with severance pay) were not affected by the severance pay reform.

samples of workers hired by mass-layoff firms. Panel A repeats the results of the our baseline sample for comparison, Panel B splits the baseline sample by gender. In Table 3 above, we have seen that the percentage female was the only variable which showed a marginally significant discontinuous change at the policy threshold—under the new regime, fewer women were hired by firms with a subsequent mass layoff. However, the results in Panel B show that reform effects are almost equally large for females as for males. In particular, transitions to new jobs are affected almost equally, while for women but not for men, there is an increase transitions to unemployment.

Table 4.4: RD diff-in-diff estimates: baseline workers vs matched controls

	(1) Treatment	(2) Control	(3) Treatment - Control
Panel A: All exits			
Post-reform	0.124***	-0.0175	0.142***
	(0.0384)	(0.0245)	(0.0437)
Pre-reform mean	0.316	0.419	0.367
Effect relative to pre-reform mean	0.393	-0.0417	0.385
Panel B: Job-to-Job			
Post-reform	0.0785***	-0.0144	0.0929***
	(0.0215)	(0.0227)	(0.0302)
Pre-reform mean	0.136	0.193	0.165
Effect relative to pre-reform mean	0.575	-0.0744	0.564
Panel C: Job-to-Unemployment			
Post-reform	0.0421**	-0.0100	0.0522*
	(0.0214)	(0.0147)	(0.0267)
Pre-reform mean	0.156	0.199	0.177
Effect relative to pre-reform mean	0.271	-0.0504	0.294
Specification			
Bandwidth(quarters)	24	24	24
Linear	Yes	Yes	Yes
Observations	26841	26841	53682

Note: The table compares RD estimates for workers in the baseline sample (column 1) to "matched control" workers (column 2) and conducts a diff-in-diff RD analysis (column 3). Matched controls are workers hired by a firm that did *not* subsequently experience a mass layoff. For each worker in the baseline sample, we look for exact matches in terms of the following characteristics: hired in the same quarter and stayed on the job for at least 12 months; same gender; same region (9 "Bundeslaender"); same industry (21 categories); same age decile. If we obtain multiple controls, we take the one with the closest propensity score based on experience, experience squared, employment status in the four quarters preceding the current job, and decile of the starting wage. 4.5 percent (out of 28,099 workers) in the baseline sample could not be matched and were dropped. We end up with 26,841 matched pairs. Inference is based on a bootstrap (1000 replications), clustered at the firm level. The RD diff-in-diff estimates are in line with previous results and confirm the hypothesis that the new system generates a stronger incentive to move to a new job for workers with a high firing probability (baseline sample)—but not for other workers (matched controls).

Panel C varies the selection of workers entering firms before a mass layoff. In our baseline specification, we look at workers entering 3 to 4 years before a mass layoff. If we either look at workers entering 3 to 3.5 years before (6 months) or 3 to 5 years before (24 months), we find a significant increase in all separations, the larger part of which is again due to higher transitions to a new job. However, we find a somewhat larger effect on transitions to unemployment.

In Panel D we present RD estimates when we increase the employment reduction criterion for a mass layoff to 66 percent and 100 percent, largely mirroring the previous graphical analysis in Figure 4.7. We continue to find a large reform effects on job separations, which are entirely driven by a higher incidence of job-to-job moves. Transitions to unemployment are small and insignificant.

Table 4.5: RD estimates: further robustness checks

	All exits	JTJ	JTU	Observations
Panel A: Baseline Results				
Baseline coefficient	0.125***	0.0803***	0.0414*	28099
	(0.0371)	(0.0200)	(0.0220)	
Panel B: According to gender				
Only male	0.123***	0.0726***	0.0363	13775
	(0.0426)	(0.0251)	(0.0272)	
Only female	0.127***	0.0788***	0.0571**	14324
	(0.0428)	(0.0235)	(0.0257)	
Panel C: According to width of mass layoff window				
24 months	0.0967***	0.0569***	0.0336**	53550
	(0.0263)	(0.0149)	(0.0156)	
6 months	0.156***	0.0991***	0.0564*	14677
	(0.0456)	(0.0233)	(0.0303)	
Panel D: According to size of mass layoff				
At least 66% reduction	0.0921**	0.0873***	-0.00176	20576
	(0.0409)	(0.0275)	(0.0210)	
Firm closure	0.0962***	0.0720***	0.0222	13011
	(0.0292)	(0.0187)	(0.0193)	
Panel E: According to distance to mass layoff, exit by one month before mass layoff window				
Entry 24 – 35 months before mass layoff	0.00677	0.00219	-0.00347	26244
	(0.0191)	(0.0137)	(0.0116)	
Entry 48 – 59 months before mass layoff	0.0880**	0.0519***	0.0275	26668
	(0.0371)	(0.0201)	(0.0210)	
Panel F: According to minimum firm size 1 month before mass layoff				
At least 15 employees	0.108***	0.0696***	0.0337*	34182
	(0.0344)	(0.0183)	(0.0201)	
At least 60 employees	0.136***	0.0856***	0.0479*	22860
	(0.0427)	(0.0235)	(0.0257)	

Note: The robustness checks are based on alternative samples of workers hired by mass-layoff firms. Panel A repeats the results based on our baseline sample for comparison, Panel B splits the baseline sample by gender, Panel C varies the selection of workers entering firms before a mass layoff. In our baseline specification, we look at workers entering 3 to 4 years before a mass layoff, while we now consider either workers entering 3 to 3.5 years before (6 months) or 3 to 5 years before (24 months). Panel D increases the required employment reduction to 66 percent and 100 percent (sticking to the baseline time window of 1 month). Panel E varies the sample selection criterion for workers. In the baseline, we select workers that entered the firm 36-47 months before the subsequent mass layoff, in Panel E this time interval is changed to 24-35 and 48-57 months, respectively. Finally, Panel F varies the sample selection criterion for mass layoff firms. In the baseline, we include only firms that had at least 30 employees one month prior to the mass layoff; in Panel F we change minimum firm size to 15 and 60 employees, respectively. Inference is based on a bootstrap (1000 replications), clustered at the firm level. The robustness checks confirm the baseline result. The severance pay reform leads to higher job separations—mainly because of higher job-to-job transitions under the new system.

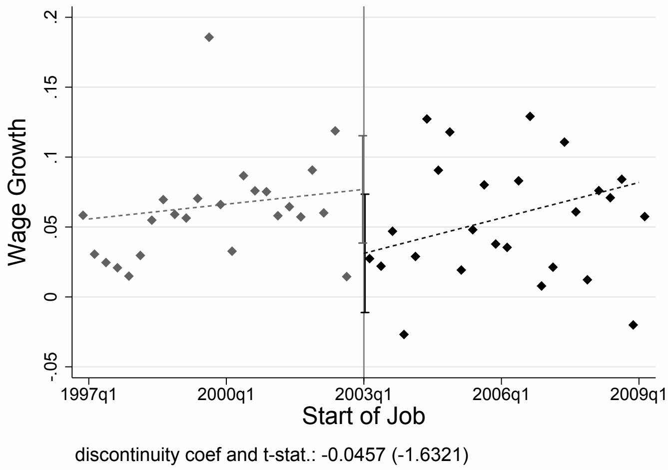
Panel E varies the sample selection criterion for workers. In the baseline, we select workers that entered the firm 36-47 months before the subsequent mass layoff, in Panel E this time interval is changed to 24-35 and 48-57 months, respectively. We change the treatment variable to, respectively, "left the firm before tenure 24 months" or "48 months". Interestingly, we do not find any significant effect of the reform on job mobility of workers who entered the firm 24-35 months before the mass layoff. Recall that workers became eligible for the severance payment only after at least 36 months of tenure. Since the mass layoff already took place before these workers became eligible for the severance pay, we should actually not expect any reform effect for this group. In contrast, workers who entered 48-57 months before the mass layoff had this incentive—and for them, we see a similar response as in the baseline sample.

Finally, Panel F of Table 5 varies the sample selection criterion for mass layoff firms. In the baseline, we include only firms that had at least 30 employees one month prior to the mass layoff; in Panel F we change minimum firm size to 15 and 60 employees, respectively. The robustness checks confirm the baseline result. The severance pay reform leads to higher job separations—mainly because of higher job-to-job transitions under the new system.

Further results. Figure 9 and Table 6 suggest that the wage increases among job changes (JTJ transitions) are smaller under the new regime. This is in line with incentives, as workers waiting for a future severance payment require higher outside offers to be induced to switch jobs. However, while the point estimates are consistently negative and of a similar order of magnitude, they are not very precisely estimates and statistically insignificant in most cases. One potential reason for this might be that we have to restrict our sample to a small subset ($N = 4280$) as we have to concentrate on workers having left before the mass layoff by a JTJ transition.

Figure 4.10 and Table 4.7 look at the incentive to wait for retirement. As explained above, workers subject to the old system were eligible for a severance pay of at least 4 monthly wages if they quit into retirement with at least ten years of tenure. Thus, old-system workers close to retirement, unlike new-system workers, should have an incentive to stay with the current employer until retirement. In order to explore this question, we consider workers aged 40 to 51 when entering a job (early retirement age is 55 (60) for women (men), while women (men) become eligible for old age pensions at 60 (65)), and look at the fraction employed for at least 10 years. Since under the old system also quits were eligible, we do *not* condition on a subsequent mass layoff and instead use the entire sample. We do not find any statistically or economically significant results.

Figure 4.9: Wage growth of job changers (JTJ), by date of job start



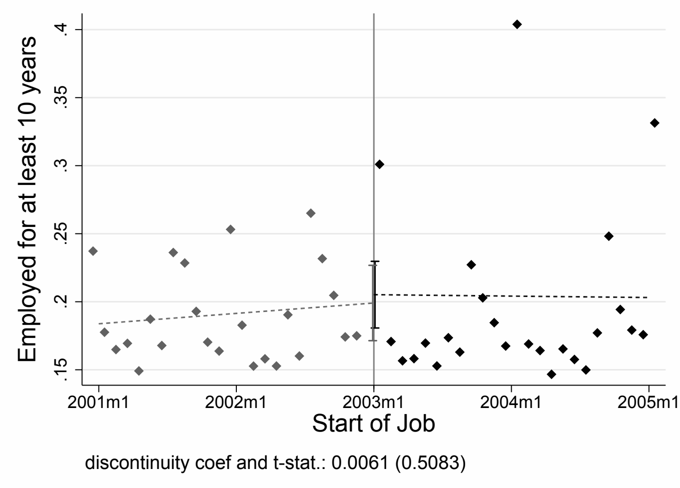
Note: The figure reports the difference in log earnings in the new job and the previous job (in the mass-layoff firm). Only workers classified as job-to-job changers leaving the firm before the mass layoff occurs are considered. Inference is based on a bootstrap (1000 replications), clustered at the firm level. Under the old system, the incentive to change jobs is lower because voluntary quitters give up their severance pay option. Under the new system, voluntary quitters do not suffer such a loss. Hence, lower wage increases are required to induce new-system workers to accept outside job offers. The figure shows that there is indeed at negative jump in average wage growth of job changes at the reform date (2003q1), although the effect is not statistically significant.

Table 4.6: Wage growth of job changers (JTJ), RD estimates

	(1)	(2)	(3)	(4)	(5)
Post-reform	-0.0457*	-0.0433	-0.0274	-0.0564	-0.0383
	(0.099)	(0.251)	(0.261)	(0.172)	(0.349)
Linear	Yes	Yes	Yes	Yes	Yes
Quadratic	No	Yes	No	No	No
Controls	No	No	Yes	No	Yes
Bandwidth (quarters)	24	24	24	8	8
Observations	4280	4280	4280	1435	1435

Note: The table reports the RD estimate of the effect of the severance pay reform on the difference in log earnings between the new job and the previous job (in the mass-layoff firm). Only workers classified as job-to-job changers leaving the firm before the mass layoff occurs are included in the regression. The hypothesis is that, under the new system, lower wages increases are required to induce workers to accept an outside offer. The estimated reform effect is indeed negative (though not statistically significant) in all regressions. Bootstrapped standard errors (1000 replications), clustered at the firm level, are reported in parentheses. Controls are gender, age, age squared, experience, experience squared, Austrian nationality, log firm size 24 months before mass layoff, manufacturing sector, Vienna, and quarter of job entry. $*(p < 0.10), **(p < 0.05), ***(p < 0.01)$

Figure 4.10: Probability of tenure larger than 10 years, by date of job start



Note: The figure explores whether the severance-pay reform affected the incentive to wait for retirement. Inference is based on a bootstrap (1000 replications), clustered at the firm level. Under the old system, workers were eligible for severance pay if they quit the job for retirement, thus there was an incentive to wait for retirement at the firm. The graph looks at workers between 40 and 51 years old who started a new job in the respective quarter. Outcome variable is an indicator whether the job lasted for more than 10 years. The underlying sample includes all job starters (and does *not* condition on a subsequent mass layoff). The figure does not indicate any major discontinuity at the reform date. If at all, there is an upward jump in the probability to stay with the firm for more than 10 years. This suggests that the abolished incentive to wait for retirement of the reform did not result in lower tenure for workers close to retirement that are subject to the new system.

Table 4.7: Dependent variable: Probability of tenure < 10 years (age at entry between 40 and 51 years)

	All exits	JTJ	JTU
Estimated coefficient	-0.00613	0.00296	-0.00909
	(0.0113)	(0.00613)	(0.00950)
Linear	Yes	Yes	Yes
Pre-reform mean	0.807	0.247	0.560
Effect relative to pre-reform mean	-0.008	0.012	-0.016
Bandwidth (quarters)	24	24	24
Observations	299975	299975	299975

Note: The table reports the coefficient β_1 from a linear probability model based on equation (4.1). The dependent variable is an indicator taking the value 1 if a worker stays with the firm for at least 10 years. We consider workers aged 40 to 51 at the time of the job start, bu do *not* restrict to firm experiencing mass layoffs. The results indicate no statistically or economically significant response. Standard errors are bootstrapped (1000 replications) and clustered at firm level. Controls are gender, age, age squared, experience, experience squared, Austrian nationality, log firm size 24 months before the mass layoff, and indicators for manufacturing sector, Vienna, and quarter of job entry; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.6 A Model of the Severance Payment Reform

In this section we will try to rationalize our previous empirical findings using a simple model of the severance payment reform.

Environment. Time is discrete. There is a continuum of risk-neutral workers of mass 1 who are either employed or unemployed. Production features constant returns to scale. If employed, a worker produces with productivity $p \in [\underline{p}, \overline{p}]$.[7] Productivity at the firm-level evolves according to a Markov process and is i.i.d. across firms. At the beginning of a period, firms can dissolve matches. In this case, a payment ψ has to be made to the worker, if he is eligible. Workers in a match start out as non-eligible and become eligible with probability α every period. At the end of a period, workers receive outside offers with endogenous probability χf, where χ denotes employees' search effort relative to the unemployed, and decide whether to accept them (in which case they do not receive a payment ψ). In addition, matches are dissolved exogenously with probability λ. The unemployed receive benefits b every period, meet vacant firms with probability f and decide whether to accept their offer.

Everyone can set up a firm, meaning that vacancies have value zero ex-ante. Vacant firms draw initial productivity from the unconditional productivity distribution and either meet unemployed or employed workers with some (endogenous) probability. These workers will then decide whether to accept the firms offer or turn it down. Wages are set by Nash bargaining.

Firm and worker decisions. The model makes predictions regarding the firms' decision to close down and the workers' decision to accept outside offers. We denote by $\gamma_i(p) \in \{0, 1\}$ the endogenous firm closure decision given productivity p and eligibity status i of the worker, where i takes the value 1 if a worker is eligible for severance pay. Moreover, let $\mu_i^j(p, p^o)$ indicate the endogenous decision of a worker with current eligibility status i employed by a firm facing productivity p to accept an outside offer by a firm facing productivity p^o where she will have eligibility status j. Given our assumption that a worker turns eligible with probability α every period, the overall probability that a worker accepts an outside offer given productivity p and eligibility status i is given by

$$\bar{\mu}_i(p) = \int_{\underline{p}}^{\overline{p}} \alpha\mu_i^1(p, p^o) + (1 - \alpha)\mu_i^0(p, p^o)\, dG(p^o),$$

[7] In the following, we will refer to the state variable p as "productivity". A different interpretation would be that firms are subject to demand shocks, which could be captured by assuming that a worker produces one unit per period which is sold at price p. This would not change the model in any way.

where $G(p^o)$ denotes the distribution of outside offers, i.e. the unconditional productivity distribution. Similarly, denote by $\mu_u^j(p^o)$ the endogenous decision by an unemployed worker to accept an offer by a firm facing productivity p^o where she will have eligibility status j and define the overall probability as

$$\bar{\mu}_u = \int_{\underline{p}}^{\overline{p}} \alpha\mu_u^1(p^o) + (1-\alpha)\mu_u^0(p^o)\, dG(p^o).$$

Bellman equations. Denote by $J_0(p)$ and $J_1(p)$ the value of a firm employing a non-eligible or eligible worker, respectively, and facing productivity p. Likewise, denote by $W_0(p)$ and $W_1(p)$ the value of a non-eligible or eligible worker, respectively, employed by a firm with productivity p. We assume that firms have to pay ψ to an eligible worker if bargaining breaks down. As the value of a vacancy is 0, firms' outside value is $0-\psi = -\psi$. Workers' outside value is $U+\psi$.[8] The common surplus, $S_1(p)$ is then given by

$$S_1(p) = (W_1(p) - (U+\psi)) + (J_1(p) - (-\psi)) = W_1(p) - U + J_1(p).$$

Nash bargaining implies

$$W_1(p) - (U+\psi) = \beta S_1(p) \text{ and } J_1(p) + \psi = (1-\beta)S_1(p),$$

where β denotes workers' bargaining power. Similarly, the surplus if the worker is not eligible, $S_0(p)$, is given by

$$S_0(p) = W_0(p) - U + J_0(p)$$

and

$$W_0(p) - U = \beta S_0(p) \text{ and } J_0(p) = (1-\beta)S_0(p).$$

All equilibrium objects can be characterized as functions of the surplus functions. In Appendix B we specify the workers' and firms' Bellman equations. Denote by δ the discount rate, and by $F(p'|p)$ the conditional distribution of a future productivity realization p' given that current productivity is p. Using the bargaining assumption, we show that the surplus functions satisfy (throughout, primes denote next period values)

$$S_1(p) = p - b + \delta f O_1(p) + \delta(1-\lambda-\chi f\bar{\mu}_1(p)) \int_{\underline{p}}^{\overline{p}} (1-\gamma_1(p'))S_1(p')dF(p'|p) \quad (4.2)$$

[8] One potential alternative assumption adopted by Saint-Paul (1995) is to assume U and $-\psi$ for the workers' and firms' outside values, respectively, based on the rationale that each party receives the payment she would receive if having initiated the separation. This coordination failure can lead to multiple equilibria and proved to be less stable in the structural estimation to follow. We thus opted for the more parsimonious approach. However, the basic mechanism still goes through, as we discuss in footnote 10.

and

$$S_0(p) = p - b + \delta f O_0(p)$$
$$+ \delta(1 - \lambda - \chi f \bar{\mu}_0(p)) \int_{\underline{p}}^{\overline{p}} \alpha(1 - \gamma_1(p'))S_1(p') + (1 - \alpha)(1 - \gamma_0(p'))S_0(p')dF(p'|p). \quad (4.3)$$

Both surplus functions consist of a flow payoff $p - b$, the workers' object value due to potential job-to-job transitions $\delta f O_i(p)$, as well as the continuation value, taking into account exogenous and endogenous separations. The object values satisfy

$$O_i(p) = \int_{\underline{p}}^{\overline{p}} \alpha(\chi\mu_i^1(p, p^o) - \mu_u^1(p^o))(\beta S_1(p^o) + \psi) + (1-\alpha)(\chi\mu_i^0(p, p^o) - \mu_u^0(p^o))\beta S_0(p^o)\, dG(p^o),$$

where $i \in \{0, 1\}$.

A firm with a non-eligible or eligible worker shuts down if $J_0(p) < 0$ or $J_1(p) < -\psi$, respectively. Using the bargaining assumption, the decision rules to shut down the firm, γ_0 and γ_1, are hence given by

$$\gamma_0 = \mathbb{1}\{S_0 < 0\} \text{ and } \gamma_1 = \mathbb{1}\{S_1 < 0\}.$$

That is, due to the bargaining assumption, it does not matter whether we think of a lay-off as firm- or worker-induced, since both parties choose to shut down the firm as soon as the joint surplus falls below zero.

Moreover, a worker receiving an outside offer trades off the outside value, given by either $W_0(p^o)$ or $W_1(p^o)$, against the value of staying, given by

$$\int_{\underline{p}}^{\overline{p}} \gamma_1(p')(U + \psi) + (1 - \gamma_1(p'))W_1(p')\, dF(p'|p)$$

if eligible or

$$\int_{\underline{p}}^{\overline{p}} \alpha\left[\gamma_1(p')(U + \psi) + (1 - \gamma_1(p'))W_1(p')\right] + (1-\alpha)\left[\gamma_0(p')U + (1 - \gamma_0(p'))W_0(p')\right]\, dF(p'|p)$$

if non-eligible. Using the bargaining assumption, we can easily show that the decision rules of the worker satisfy

$$\mu_0^0(p,p^o) = \mathbb{1}\left\{\beta S_0(p^o) > \alpha\psi + \int_{\underline{p}}^{\overline{p}} \alpha(1-\gamma_1(p'))\beta S_1(p') + (1-\alpha)(1-\gamma_0(p'))\beta S_0(p')\, dF(p'|p)\right\}$$

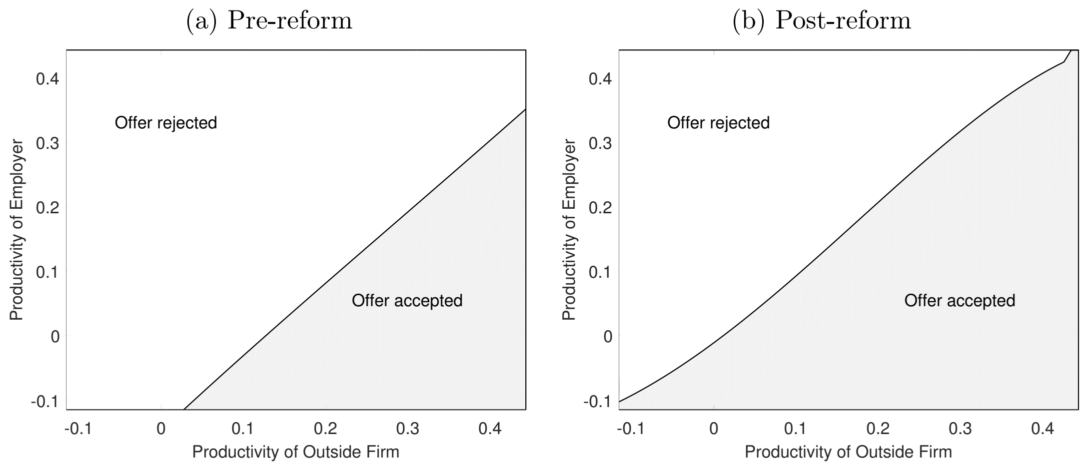
$$\mu_0^1(p,p^o) = \mathbb{1}\left\{\beta S_1(p^o) + \psi > \alpha\psi + \int_{\underline{p}}^{\overline{p}} \alpha(1-\gamma_1(p'))\beta S_1(p') + (1-\alpha)(1-\gamma_0(p'))\beta S_0(p')\, dF(p'|p)\right\}$$

$$\mu_1^0(p,p^o) = \mathbb{1}\left\{\beta S_0(p^o) > \psi + \int_{\underline{p}}^{\overline{p}} (1-\gamma_1(p'))\beta S_1(p')\, dF(p'|p)\right\}$$

$$\mu_1^1(p,p^o) = \mathbb{1}\left\{\beta S_1(p^o) + \psi > \psi + \int_{\underline{p}}^{\overline{p}} (1-\gamma_1(p'))\beta S_1(p')\, dF(p'|p)\right\}.$$

ψ enters the decision rules in a very transparent way. Clearly, a higher ψ makes workers more reluctant to switch jobs when eligible. Figure 4.11 gives a summary of the model's predictions regarding worker behavior before and after the reform:[9] Before the reform, a worker had to be compensated for forgoing a severance payment and hence a firm making an outside offer had to have a much higher productivity. After the reform, workers are also willing to move to firms that are weakly more productive.

Figure 4.11: Offer acceptance rule before and after the reform (eligible workers)



Note: The plots show the acceptance rule of outside offers for eligible workers given productivity of the current employer and productivity of the outside firm. The plots are outcomes of the estimated model to be described later in the text.

The decision rules for the unemployed are given by

$$\mu_u^0 = \mathbb{1}\{\beta S_0(p^o) > 0\}$$
$$\mu_u^1 = \mathbb{1}\{\beta S_1(p^o) + \psi > 0\}.$$

[9]Figures 4.11 and 4.12 have been generated using the parameterization based on the baseline estimates described later on.

How can a severance payment have an effect in our setting? First, note that absent endogenous job-to-job transitions by workers, the surplus equations would not be affected by severance payments. Due to Nash bargaining, the wages would completely offset the effect, which is reminiscent of the Lazear (1990) result. Even if we allowed for job-to-job mobility, severance pay would be inconsequential if eligibility for severance pay was universal—the special case $\alpha = 1$ in our model—as is usually assumed when modeling lay-off taxes. In this case, severance pay would again just correspond to a deferred payment and be offset by wages. However, mirroring a prominent feature of most severance payment rules around the world, we assume that eligibility relates to tenure. This breaks the neutrality result, as severance pay is allowed to affect worker mobility: Currently eligible workers know that they will lose their eligibility status with probability $1 - \alpha$ in any outside offer, in which case their outside value drops from $U + \psi$ to U, while firms outside value increases from $-\psi$ to 0, leading to a lower bargained value *ceteris paribus*. Hence, workers facing a high ψ are more reluctant to accept outside offers.[10]

How does this feed back into the firm closure decisions, the second important behavioral margin of the model? The effect of higher worker mobility on the surplus is generally ambiguous: To get some intuition, consider the effect of an increase in μ_1^0 and μ_1^1 on $S_1(p)$, assuming they will move back to their old values in the subsequent period:

$$\begin{aligned}\Delta S_1(p) = \delta\chi f \int_{\underline{p}}^{\overline{p}} & \alpha\Delta\mu_1^1(p,p^o)\left[\beta S_1(p^o) + \psi - \int_{\underline{p}}^{\overline{p}} (1-\gamma_1(p'))S_1(p')dF(p'|p)\right] \\ & + (1-\alpha)\Delta\mu_1^0(p,p^o)\left[\beta S_0(p^o) - \int_{\underline{p}}^{\overline{p}} (1-\gamma_1(p'))S_1(p')dF(p'|p)\right] dG(p^o)\end{aligned}$$

As is apparent, the sign of the effect depends on how $\beta S_1(p^o) + \psi$ or $\beta S_0(p^o)$ compare to the continuation surplus in the current firm. On the one hand, a moving worker only takes into account *her* part of the surplus in the decision, while ignoring the part accruing to the firm. On the other hand, the worker's part of an outside offer might still be more than the entire expected surplus in the current firm if the current surplus is very low.

[10] This is the crucial link in the model which would be preserved even if we used Saint-Paul (1995)'s assumption discussed in footnote 8. While in our case the surplus of workers relative to the surplus of firms is given by

$$W - U = \frac{\beta}{1-\beta}J + \frac{\psi}{1-\beta},$$

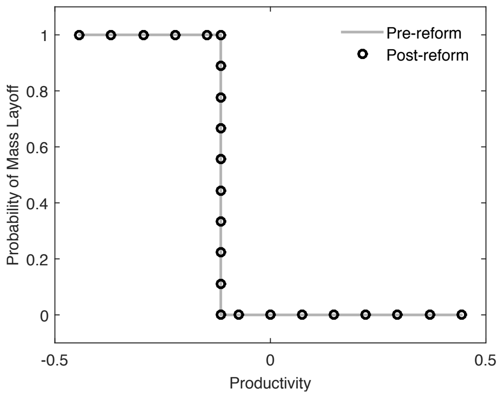
the respective expression following Saint-Paul (1995) reads

$$W - U = \frac{\beta}{1-\beta}J + \frac{\beta}{1-\beta}\psi.$$

Hence, even if their outside value is not affected, workers still manage to improve their bargaining position with a high ψ as the firms' outside value is lower.

Given a high worker mobility, workers in bad matches realize they have a high option value. They will rebate part of this option value to their employer by accepting lower wages. This implies that firms facing low prices can survive by paying lower wages. While the former would tend to lead to a lower surplus, the latter would increase the surplus. In Figure 4.12, we plot the policy function for a firm with an eligible worker implied by our baseline estimates.[11] As is apparent, given the 101-state grid we apply, the two effects cancel each other out and the firm's policy function is unaffected.

Figure 4.12: Probability of mass layoff before and after the reform



Note: This figure shows the optimal decision to close down as function of productivity for a firm with an eligible worker, $\gamma_1(p)$. As explained later in the text, $\gamma_1(p)$ has to be smoothed for the estimation. The graph is obtained by re-dichotomizing the smoothed policy function using the rule $\mathbb{1}\left[\gamma_1(p) > 0.5\right]$.

Stationary employment distribution. In order to derive the zero-profit condition, which involves the probability of meeting a worker currently employed at a firm with productivity p, we need to solve for the stationary productivity distribution. In particular, denote by $n_0(p)$ and $n_1(p)$ the stationary number of non-eligible and eligible workers employed at a firm with current productivity p. Since there is a unit measure of workers, the unemployment rate satisfies $u = 1 - \int_{\underline{p}}^{\overline{p}} n_0(p) + n_1(p)\, dp$.

$n_0(p)$ and $n_1(p)$ satisfy the following properties: For all $p' \in \left[\underline{p}, \overline{p}\right]$,

$$
\begin{aligned}
n_0(p') = {} & (1-\gamma_0(p'))(1-\alpha)\int_{\underline{p}}^{\overline{p}} (1-\chi f \bar{\mu}_0(p) - \lambda) n_0(p) f(p'|p)\, dp \\
& + (1-\alpha) f u \mu_u^0(p') g(p') + (1-\alpha)\chi f \int_{\underline{p}}^{\overline{p}} (n_0(p)\mu_0^0(p,p') + n_1(p)\mu_1^0(p,p')) g(p')\, dp
\end{aligned}
\tag{4.4}
$$

[11] As we will explain later on, we smooth the policy functions following standard practices to make estimation feasible. To produce Figure 4.12, we re-dichotomized the continuous $\gamma_1(p)$ using the rule $\mathbb{1}\left[\gamma_1(p) > 0.5\right]$. The smoothed $\gamma_1(p)$ before and after the reform are not entirely equal, but the difference is minimal, leading to unchanged dichotomized policy functions.

and

$$
\begin{aligned}
n_1(p') = (1-\gamma_1(p')) \int_{\underline{p}}^{\overline{p}} (1-\chi f \bar{\mu}_1(p) - \lambda) n_1(p) f(p'|p)\, dp \\
+ \alpha f u \mu_u^1(p') g(p') + \alpha \chi f \int_{\underline{p}}^{\overline{p}} (n_0(p)\mu_0^1(p,p') + n_1(p)\mu_1^1(p,p')) g(p')\, dp \\
+ (1-\gamma_1(p'))\alpha \int_{\underline{p}}^{\overline{p}} (1-\chi f \bar{\mu}_0(p) - \lambda) n_0(p) f(p'|p)\, dp, \quad (4.5)
\end{aligned}
$$

where $g(p)$ is the p.d.f. of initial productivity draws. A non-eligible worker currently employed at a firm with productivity p' was either employed at the firm before and not laid off, or entered it from unemployment or a different job. An eligible worker was either employed before or promoted to be eligible.

Zero profit condition. The number of meetings between a vacant firm and a potential employee is determined by the meeting function

$$m = m(u + \chi(1-u), v),$$

where v denotes the number of vacancies. Define labor market tightness $\theta \equiv \frac{v}{u+\chi(1-u)}$. Assuming that $m(u+\chi(1-u), v)$ satisfies constant returns to scale, we can write for the probability that a vacant firm meets a worker, q,

$$q = \frac{m}{v} = m(\theta^{-1}, 1) \equiv q(\theta) \text{ with } q'(\theta) < 0.$$

The probability of meeting an unemployed person is given by $qu/(u+\chi(1-u))$, whereas the probability of meeting an employed person is given by $q\chi(1-u)/(u+\chi(1-u))$. The probability that an unemployed person meets a firm, f, can be written

$$f = \frac{m}{u+\chi(1-u)} = m(1,\theta) \equiv f(\theta) \text{ with } f'(\theta) > 0,$$

while the probability that an employed person meets a firm is given by χf.

Denote by $a_i(p^o)$ the probability that, upon meeting an unemployed or employed worker, an offer by a firm with initial productivity p^o and status $i \in \{0,1\}$ is accepted. It is given by

$$a_i(p^o) = \frac{u}{u+\chi(1-u)} \cdot \mu_u^i(p^o) + \frac{\chi(1-u)}{u+\chi(1-u)} \cdot \frac{\int_{\underline{p}}^{\overline{p}} n_0(p)\mu_0^i(p,p^o) + n_1(p)\mu_1^i(p,p^o) dp}{1-u},$$

where the first term is the conditional probability of meeting an unemployed worker times the probability that the worker accepts, while the second term is the conditional probability of meeting a currently employed worker times the probability that she will accept the outside offer.

The expected value of a vacancy, V, satisfies

$$V = -c + \delta q(\theta) \int_{\underline{p}}^{\overline{p}} (1-\alpha) a_0(p^o) J_0(p^o) + \alpha a_1(p^o) J_1(p^o)\, dG(p^o).$$

A vacant firm pays hiring costs c every period. With probability q the firm meets a potential worker and draws initial productivity p^o from the distribution $G(p^o)$, while the worker becomes eligible with probability α. If the offer is accepted, the firm can start producing in the subsequent period, yielding value $J_i(p^o)$.

Due to free entry, a vacancy has to yield zero expected profits, i.e. $V = 0$. In terms of the surplus functions, this implies

$$\frac{c}{\delta q(\theta)} = \int_{\underline{p}}^{\overline{p}} (1-\alpha) a_0(p^o)(1-\beta) S_0(p^o) + \alpha a_1(p^o)((1-\beta) S_1(p^o) - \psi)\, dG(p^o) \tag{4.6}$$

pinning down $\theta, q,$ and f. We have to point out one subtlety here: If α or ψ are very large, the right-hand side of (4.6) is not guaranteed to be positive. Indeed, given extremely high firing restrictions, firms may not find it worthwhile to post vacancies. In this case, an equilibrium is not defined.

Equilibrium. In equilibrium, firms and workers have rational expectations and choose their strategies optimally, meaning that the surplus functions $S_0(p)$ and $S_1(p)$ solve the recursive equations (4.2) and (4.3). Moreover, vacancies yield zero profit, taking as given optimal behavior by firms and workers and the stationary employment distribution. Definition 4.1 summarizes the equilibrium conditions.

Definition 4.1. *An equilibrium is given by functions* $\{n_0(p), n_1(p)\}$*, values* $\{S_0(p), S_1(p)\}$ *and labor market tightness* θ *such that*

1. $\{S_0(p), S_1(p)\}$ *solve the recursive equations (4.2) and (4.3);*
2. $\{n_0(p), n_1(p)\}$ *solve the recursive equations (4.4) and (4.5);*
3. *labor market tightness* θ *solves the zero-profit condition (4.6).*

Note that the bargaining assumption is not as restrictive as it might appear. In particular, the model's structure does not require bargaining every period. In fact, the equilibrium is only affected by β due to the formation of new matches: On the one hand, the surplus functions depend on β as it determines the share of the new match surplus which is captured by workers when they move to a new job. On the other hand, firms' vacancy creation depends on their share of the surplus. It does not matter, however, whether this share of the match is preserved in ongoing matches every period, since the definition of the equilibrium will not be affected. Instead, we can interpret β as the share of the match surplus that a worker expects to receive *on average* over all future periods when entering a new match. The only additional assumption we need then is that renegotiation takes place if either margin of the bargaining range is hit (see Malcomson (1997)).

Transition. Definition 4.1 allows us to derive steady states for the pre- and post-reform period given a set of parameters. However, given that we compare workers close to the reform cutoff in our RDD setting, a comparison of steady states might not give us useful predictions. Indeed, two workers, one of them having entered in December 2002 and the other in January 2003, arguably face very similar outside opportunities when the firm is close to a mass layoff about three years later. Moreover, while the pre-reform steady state presumes that workers expect to stay in the old system forever, a worker in an old-system match having surpassed the reform threshold knows that any future match will be subject to the new system.

To account for these issues, we will have to allow for the transition between the old and the new steady state. To see how this can be done, first note that labor market tightness is the only state variable on the macro level. As the economy moves from the old to the new steady state, labor market tightness moves from its old to its new equilibrium value. If we fix θ and hence f, all policy functions characterizing firms' and workers' optimal behavior follow in partial equilibrium, as can be seen from equations (4.2) and (4.3). New-system workers know that any future match will also be subject to the new system and hence their Bellman equations do not change. Old-system workers, on the other hand, take into account that they switch to the new system in any new match. For instance, denoting by tilde values in transition and calling $\tilde{S}^{new}(p^o)$ the surplus of a match with a new-system worker, the surplus of an eligible old-system worker in transition satisfies

$$\tilde{S}_1^{old}(p) = p - b + \delta f \int_{\underline{p}}^{\overline{p}} (\chi \tilde{\mu}_1^{old}(p, p^o) - \tilde{\mu}_u(p^o))\beta \tilde{S}^{new}(p^o)\, dG(p^o)$$
$$+ \delta(1 - \lambda - \chi f \bar{\tilde{\mu}}_1^{old}(p)) \int_{\underline{p}}^{\overline{p}} (1 - \tilde{\gamma}_1^{old}(p'))\tilde{S}_1^{old}(p') dF(p'|p).$$

In Appendix B, we show in detail how the recursive equations are affected.[12]

[12]Note that we still have to make a simplification here: We fix θ at one intermediate value, while in reality workers should take into account the actual future transition to the new steady state. Apart

4.7 Structural Estimation

Model specification. We estimate the model by Simulated Method of Moments. That is, after choosing functional forms and fixing part of the parameters of the model, we use the model to simulate artificial data sets. We then require the parameters of the model to minimize the distance between specific moments of the actual and the simulated data.

Periodicity is set to one month. We assume that productivity evolves according to

$$\log p_t = \rho \log p_{t-1} + \varepsilon_t,$$

where $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$. We approximate this process by a 101-state Markov chain using the algorithm due to Tauchen (1986). The meeting function is assumed to be of Cobb-Douglas form, i.e.

$$m(u + \chi(1-u), v) = m_0(u + \chi(1-u))^\phi v^{1-\phi}.$$

We have to choose part of the parameters exogenously, for several reasons: The level of the severance payment and the probability of becoming eligible, ψ and α, are dictated by the institutional setting. In reality, severance payments are indexed to the monthly wage before the layoff. In order to approximate this rule, we index the severance payment to $w_1(\tilde{p})$, where $\tilde{p}$ is the lowest level of productivity for which $\gamma_1(p) = 0$. We then have $\psi = \psi_w w_1(\tilde{p})$, where we set $\psi_w = 2$ to match two monthly wages for the time before the reform, while setting $\psi_w = 0$ after the reform. Moreover, we set $\alpha = 1/36$ to match an average waiting time until eligibility of three years.

Other parameters are not identified separately from other parameters of the model or typically hard to estimate. However, we find them reasonably constrained by previous choices in the literature. We set $\delta = 0.997$, which yields an annual interest rate of approximately 4%. We follow Hall and Milgrom (2008) in choosing $b = 0.71$. The meeting function elasticity ϕ is fixed at 0.6, which is the middle of the range of values reported by Petrongolo and Pissarides (2000). The condition due to Hosios (1990) then provides a natural choice for workers' bargaining power and hence we set $\beta = 0.6$. Lastly, we need to fix the autocorrelation of idiosyncratic firm shocks, ρ, for computational reasons.[13] We choose $\rho = 0.972$, so that the half-life of a shock is two years. Different choices for ρ yield

from the obvious comment that it should be very hard for workers to correctly predict the equilibrium response of the labor market, it also turned out in our estimation that the quantitative consequences when moving from a comparison of steady states to the version allowing for transition are small. Thus, the results when accounting for the actual transition of θ should not be very different, either.

[13] In particular, estimation is computationally feasible as we can keep the same set of stochastic shocks in every iteration. If we vary the standard deviation of ε_t, we just have to scale the shocks. If we varied ρ, by contrast, we would have re-generate the trajectories in every iteration.

Table 4.8: Calibrated parameters

Parameter	Definition	Value	Source/Target
δ	Discount rate	0.997	4% annual interest rate
β	Workers' bargaining power	0.600	Hosios (1990) condition
ϕ	Elasticity of q w.r.t. θ	0.600	Petrongolo and Pissarides (2000)
α	Probability of becoming eligible	0.028	3 years average waiting time
ψ_w	Severance payment per previous wage	2.000	2 monthly wages
ρ	Autocorrelation of prices	0.972	Half-life of shock 8 quarters
b	Opportunity cost of employment	0.710	Hall and Milgrom (2008)

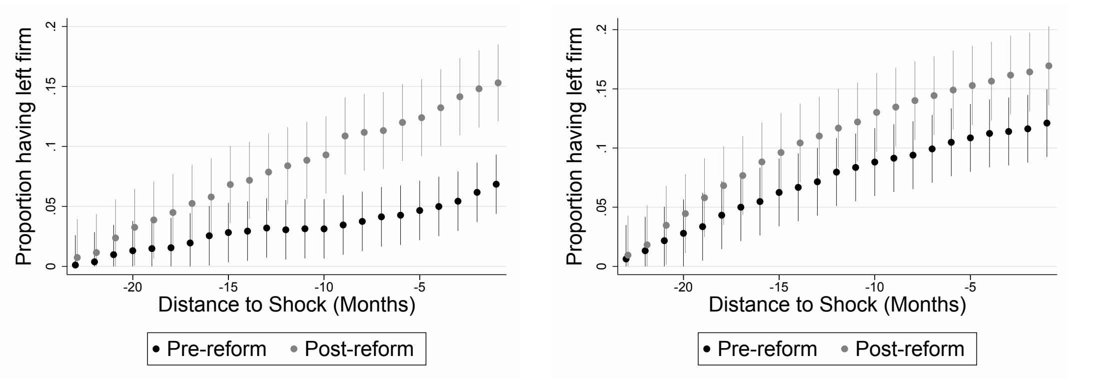
Note: The table contains the parameter values which are fixed exogenously either based on the institutional setting or based on the literature.

similar results, while we need sufficient persistence for the workers to be able to predict future mass layoffs. We summarize the parameter choices in Table 4.8.

Empirical moments. The remaining parameters of the model, that is, the exogenous separation rate λ, the standard deviation of innovations ε_t, σ_ε, relative search effort of the employed χ, the efficiency parameter of the meeting function m_0, and hiring costs c are chosen to match empirical moments.

Figure 4.13: Moments estimated from RDD

(a) Cumulative exit rates (JTJ) (b) Cumulative exit rates (JTU)



Note: The figures plot pre- and post-reform cumulative exit rates (either conditioning on a JTJ or a JTU transition) calculated from an RDD (see main text for the exact specification). The point estimates are part of the moments to be fitted. Confidence intervals are based on a bootstrap (1000 replications) clustered at the firm level.

On the one hand, we require the model to match the observed cumulative exit shares into unemployment (JTU) and to a new job (JTJ) in the months 23 to 1 before a mass layoff. As in the empirical section, we classify a transition as JTJ if the intervening period of unemployment does not exceed 28 days. Of course, this will lead us to misclassify part of the JTU transitions as JTJ. However, this is not a problem if we apply the same definition to the simulated data. In order to identify the exit rates in the data, we include workers still employed at the firm two years before the mass layoff[14] and estimate RDD regressions of the form

$$d_i(t) = \beta_0(t) + \beta_1(t)\mathbb{1}\left[x_i \geq 0\right] + \beta_2(t)x_i + \beta_3(t)x_i\mathbb{1}\left[x_i \geq 0\right] + \varepsilon_i(t),$$

where $d_i(t)$ takes the value 1 if worker i has exited the firm t periods before the mass layoff by a JTU or JTJ transition and x_i denotes the normalized start date of the job. We include 24 quarters to the left and the right of the cutoff and give more weight to observations close to the cutoff by choosing a triangular kernel. The exit rates before and after the reform are then identified as $\beta_0(t)$ and $\beta_0(t) + \beta_1(t)$, $t \in \{24, \ldots, 2\}$. We show the resulting patterns in Figure 4.13. We estimate the same RDD specification on the artificial data generated by the model. Since there is no time dimension, we allocate x_i randomly to individual observations using probability weights according the observed distribution of start dates in the data.

In addition, we require the model to match certain macro moments: Using the universe of workers observed in ASSD, we measure a monthly probability of a reduction in employment by at least 33% of 1.37%[15], a monthly job-finding rate of 15%, and an average unemployment rate (years 1994-2013) of 6.8%. Using survey data on vacancies, we calculate an average vacancy-unemployment ratio of 0.35 for the years 2009-2015 (we lack representative data on the years before). Moreover, drawing on evidence in Silva and Toledo (2009), Elsby and Michaels (2013) require expected hiring costs to equal 14% of quarterly worker compensation. Here, expected hiring costs are given by $c/(q(\theta) \cdot a)$, where a denotes the unconditional probability that an offer is accepted, and we target the same number. Since we cannot measure the macro moments separately before and after the reform due to business cycle effects, we will take an average of the simulated values before and after the reform.

The exit rates in Figure 4.13 are based on $N = 25'719$ observations ($N_0 = 14'288$ before the reform and $N_1 = 11'413$ after the reform) of workers in firms in the last two years before firm closure. For every given set of parameters, we solve for the equilibrium defined in Definition 4.1 by iterating on the equilibrium conditions pre- and post-reform. This allows us to simulate aggregate variables as well as policy functions *contingent on being in a firm about to close down.* Using these policy functions, we then simulate H

[14] As we assume constant returns and model one-person firms, our model can only generate firm closures. For our baseline results, we define the corresponding event in the data to be a mass lay-off as defined in the empirical section ($\geq$33 % reduction within one month), but we also estimated the model only including actual firm closures and the results were broadly in line (results available on request).

[15] In order to keep the model from choosing a zero probability, we target the log of this probability.

datasets of size N_0 and N_1 for the period before and after the reform, respectively, and estimate the RDD regressions and macro moments based on them.

In total, we target 97 moments (23 monthly exit rates for JTU and JTJ pre- and post-reform plus five macro moments). Call $\boldsymbol{\beta} \equiv (\lambda, \sigma_\varepsilon, \xi, m_0, c)$ the parameters to be estimated and $\tilde{m}(\boldsymbol{\beta}, e)$ the simulated moments given parameters $\boldsymbol{\beta}$ and a set of shocks e. Call m the corresponding vector of empirical moments. We choose $\boldsymbol{\beta}$ by solving

$$\min_{\boldsymbol{\beta}} \left(\tilde{m}(\boldsymbol{\beta}, e) - m\right)' W \left(\tilde{m}(\boldsymbol{\beta}, e) - m\right),$$

where W is a weighting matrix. Efficient GMM requires setting W equal to the inverse of variance-covariance matrix of m. Instead, we choose W equal to the identity matrix.[16] The reason is that we view the model rather as a description of firms about to experience a mass layoff than as a representation of the entire economy. We include macro moments to ensure that the parameters are identified and not unrealistic but do not expect the model to reproduce macro moments perfectly in line with aggregate data solely using data from firms experiencing negative shocks. In other words, we do not expect the parameters describing the behavior of these firms to be perfectly in line with the entire economy. Since the macro moments are measured with much less variance, efficient GMM will put much more weight on the macro moments, while our primary interest lies in explaining worker mobility in declining firms.

A well known problem with Method of Simulated Moments is that the simulated moments are a discontinuous function of the underlying parameters for a given set of random shocks, as we have a finite number of observations and discrete outcomes. This can pose problems to optimization algorithms, leading to non-convergence or convergence to local optima. Keane and Smith (2003) propose a remedy for this problem in the context of a random utility model: Suppose that a binary variable y_i is 1 if a simulated latent utility given parameters β, $u_i(\beta)$, is positive and zero otherwise. Instead of using y_i to calculate the simulated moments, they propose using a continuous function of the latent utility, $g(u_i; \zeta)$, where $g(u_i; \zeta) \to y_i$ as $\zeta \to 0$. Our choice for $g(u; \zeta)$ is

$$g(u; \zeta) = \Phi(u/\zeta),$$

where $\Phi(\cdot)$ denotes the c.d.f. of the standard normal distribution. Paralleling this strategy, we apply this smoothing procedure to all discrete outcomes of the model, i.e. to the policy functions $\gamma_0(p)$, $\gamma_1(p)$, $\mu_0(p, p^o)$, and $\mu_1(p, p^o)$.

There is no clear rule as to which value should be chosen for the smoothing parameter

[16] We only give weight 0.1 to expected hiring costs, as this is the only moment not based on Austrian data.

ζ and the number of simulated datasets H. Larger values of ζ and H lead to a smoother surface of the objective function, decreasing the risk of local optima where the optimization algorithm could get stuck. At the same time, increasing ζ increases the bias, while a higher H is more computationally expensive. For the results reported here, we choose $H = 5$, which still leads to manageable computation time. We then chose ζ so that the objective function is reasonably smooth.[17]

Informal discussion of identification. In this section we briefly comment on the structural features of the model and the variation in the data that helps pin down the parameters to be estimated.

- Exogenous separation rate: The exogenous separation rate is primarily identified by the exit rates into unemployment as well as equilibrium unemployment conditional on the average job-finding rate.
- Standard deviation of innovations: The volatility of firm shocks is primarily pinned down by the probability of a mass lay-off, i.e. the probability that the stochastic process hits a lower threshold.
- Relative search effort of the employed: Conditional on the job-finding rate, the relative search effort is pinned down by the exits into new jobs.
- Meeting efficiency: Meeting efficiency is pinned down by labor market tightness and the job-finding rate.
- Hiring costs: Conditional on the vacancy filling rate, hiring costs are identified by expected hiring costs per quarter.

While this intuition helps in understanding where the identification comes from, this is of course no formal criterion. As another check, we conducted extensive Monte-Carlo tests showing that the estimation mostly succeeds in recovering the true structural parameters.

4.8 Results

The estimated parameter values are presented in column 1 of Table 4.9. We estimate a monthly exogenous separation rate of 0.98%, which implies an average job duration in the absence of job-to-job transitions of approximately 8.5 years. Moreover, we estimate a standard deviation of innovations in idiosyncratic firm heterogeneity of 1.05%, which together with ρ corresponds to an unconditional standard deviation of productivity of

[17] We choose ζ as low as possible. It turned out that $\zeta = 0.2$ resulted in a reasonably smooth surface.

around 19%. Our estimates also imply that the employed have a twenty times lower probability of getting a job offer. While this might seem very low, we have to point out that this parameter not only captures differences in search effort, but also other factors which lower the probability of job-to-job transitions, such as moving costs, specific human capital, and so on.[18]

Table 4.9: Estimates

		Specification	
Parameter	Definition	Baseline	Temporary employment
λ	Exogenous separation rate	0.0098 (0.0001)	0.0098 (0.0001)
σ_ε	Standard deviation of innovations	0.0105 (0.0006)	0.0120 (0.0005)
χ	Relative search effort of the employed	0.0466 (0.0115)	0.0495 (0.0112)
m_0	Meeting efficiency	0.2527 (0.0076)	0.2140 (0.0068)
c	Hiring costs	0.3528 (0.0072)	0.3628 (0.0073)

Standard errors in parentheses

Note: This table shows the estimated parameter values obtained by estimating the baseline model (column 1) or a variant of the model allowing for temporary employment to be explained later in the text.

In Figure 4.14 we plot the simulated exit rates into unemployment and to a new job, as well as all exits, against their observed counterparts. In column 1 of Table 4.10, we additionally compare the simulated macro moments to their empirical counterparts. Overall, the fit is quite good. The estimated model captures well the qualitative finding that the difference in exit rates is mostly driven by JTJ transitions. In the data we also observe a small positive effect on JTU transitions which the model cannot replicate.[19]

The fit of the macro moments is decent, given that we have to extrapolate to the entire economy from the set of declining industries. The main discrepancy is in the expected hiring cost, which we overestimate considerably. However, we have to keep in mind that this moment might not give a good description of the Austrian case as it is based on US survey data.

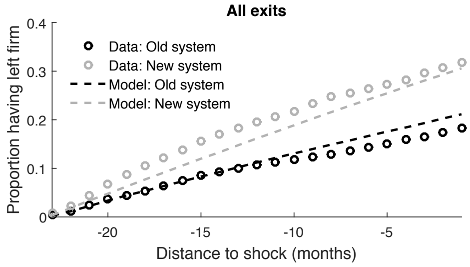
While we target the average of the pre- and post-reform equilibrium unemployment rates, the model predicts a modest decrease of unemployment from 6.54% to 5.94%, which is driven by higher job creation. Along with 0.6 percentage points increase in

[18]In fact, we have estimated a different version of the model where we fix χ to a common value in the literature and assume workers face moving costs, which are estimated. While the two models are not separately identified given the data, we obtain reasonable moving costs of around two monthly wages.

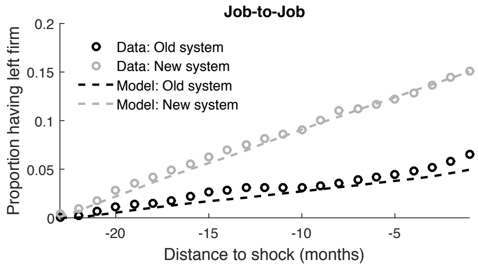
[19]One explanation for the positive effect could be that post-reform workers are more likely to quit a job in order to become self-employed. Since self-employed workers are not observed in our dataset, these workers would show up as JTU transitions. Indeed, Hacamo and Kleiner (2016) document a positive relationship between bankruptcy and subsequent entrepreneurship by former employees.

Figure 4.14: Cumulative share of workers leaving into unemployment and to another job, simulated values vs. data

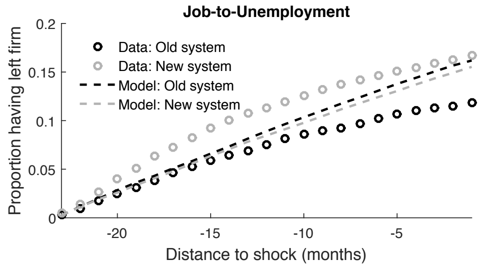
(a) Cumulative exit rates (all exits)



(b) Cumulative exit rates (JTJ)



(c) Cumulative exit rates (JTU)



Note: The figures compare cumulative exit rates implied by an RDD (see main text for details) on our baseline sample to an RDD based on artificial data generated by the model using calibrated (Table 4.8) and estimated (Table 4.9) model parameters. Figure (a) shows all exits, while figures (b) and (c) distinguish between JTJ and JTU transitions. Note that we only fit figures (b) and (c) as figure (a) corresponds to the sum of figures (b) and (c).

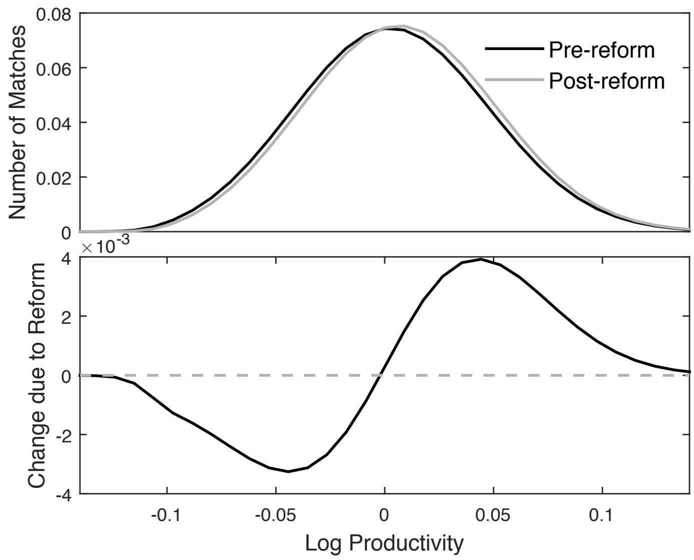
Table 4.10: Model fit: macro variables

		Simulated:	
Moment	Data	Baseline	Temporary employment
Probability of Mass Layoff	0.0137	0.0137	0.0137
Unemployment Rate	0.0680	0.0624	0.0709
Labor Market Tightness	0.3500	0.3489	0.3501
Job-Finding Rate	0.1500	0.1654	0.1865
Hiring Cost Share	0.1400	0.3505	0.3187
Share Temporary Employment	0.0400	–	0.0756

Note: The table compares observed macro moments to moments generated by the model using calibrated (Table 4.8) and estimated (Table 4.9) model parameters.

employment goes an increase in output of almost one percentage point. Thus, we also predict a productivity increase (output per worker increases by 0.33 percentage points) which is due to faster reallocation of workers from less to more productive firms. In Figure 4.15, we plot the stationary productivity distributions before and after the reform and the change in the number of matches in every productivity bin. Clearly, we observe a rightward shift as less productive firms exit the market more quickly, while more productive firms benefit from the higher arrival rate of workers. In reality, this effect might even be stronger as we have reason to believe that our model underestimates this effect.[20]

Figure 4.15: Stationary productivity distribution before and after the reform



Note: The top plot shows the stationary number of workers of either eligibility status (i.e. $n_0(p) + n_1(p)$) per productivity state implied by the model using calibrated (Table 4.8) and estimated (Table 4.9) model parameters, distinguishing between the pre- and post-reform steady state. The bottom plot shows the difference in the number of workers per productivity state between the post- and the pre-reform steady state.

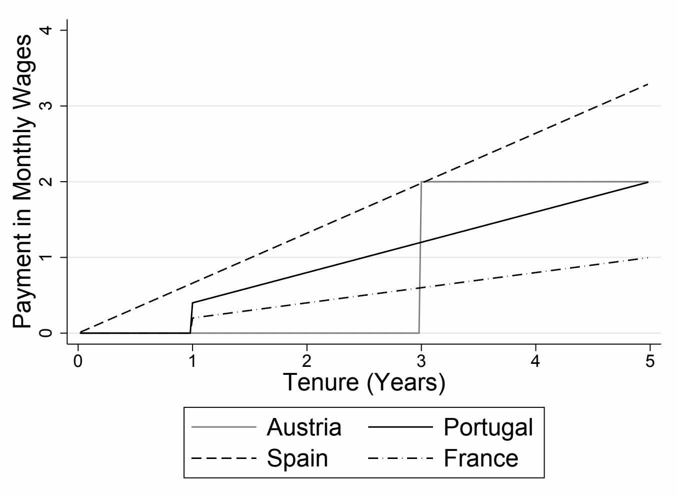
4.9 A Role Model for Southern Europe?

Inflexible labor markets are among the main culprits of the persistently high unemployment rate in Southern Europe: Given the high dismissal costs in bad times and the low arrival rate of currently employed workers, firms are reluctant to create jobs, leading to high unemployment. As mentioned above, our model predicts a moderate effect on unemployment for Austria. However, Austria's pre-reform system was more moderate than the status quo of most Southern European countries. In Figure 4.16, we plot the mandatory severance payment schemes for different Southern European countries against the Austrian case. While the level appears to be comparable, it is striking that the time to eligibility is generally lower than in Austria. However, these numbers just give an

[20]To keep the model manageable for our structural estimation, we assume that entrepreneurs that exit the market get to draw from the stationary distribution again. Thus, a very bad entrepreneur might re-enter as a very good one. In reality, bad entrepreneurs remain bad even if inactive and creative destruction should have a more persistent effect.

incomplete account of the actual dismissal costs employers face, as they do not account for potential litigation in case of unfair dismissal, which is common in these countries: In Portugal, for instance, the court fixes an amount of indemnification between 15 and 45 days per year of tenure, but at least three months of wages. Overall, the risk of litigation increases the expected size of the payment, but also entails considerable uncertainty.

Figure 4.16: Mandatory severance pay in selected countries



Note: The figure shows mandatory severance payment schemes in selected countries. The numbers are based on OECD Indicators of Employment Protection (`http://www.oecd.org/employment/emp/oecdindicatorsofemploymentprotection.htm`, and ILO Employment Protection Legislation Database ?- EPLex, `http://www.ilo.org/dyn/eplex/termmain.home`, both accessed 12/21/2016).

Baseline model. While our model cannot account for all qualitative features of the systems in different Southern European economies, we can explore the consequences of a more generous severance payment scheme by either increasing ψ, i.e. assuming a higher payment in case of an (unfair) dismissal of an eligible worker, or lowering α and thus mimicking a lower time to eligibility. All other parameters are held constant at either the calibrated values (Table 4.8) or the estimated values in Table 4.9.

The results are shown in Table 4.11. In column 1, we summarize the baseline Austrian case, where mandatory severance pay is two monthly wages and time to eligibility is 36 months. There is a moderate drop in unemployment by around 0.6 percentage points. It turns out that job destruction increases slightly, but this is more than compensated by the much higher effect on job creation. Moreover, there is an effect on output which exceeds the effect on employment, implying a productivity increase as discussed above. In column 2, we start by increasing the size of the mandatory severance payment from two to three monthly wages. As is apparent, there is a modest increase in the effect on unemployment, output and output per worker, but the broad conclusions stay unchanged.

This changes once we reduce the time to eligibility to one quarter in columns 3 and 4: There is now a marked effect on unemployment of either 3 or almost 5 percentage points. Output changes by up to 6 percentage points, accompanied by a productivity increase of up to 0.66 percentage points.

Table 4.11: Simulation results (baseline)

	Scenario:			
Time to eligibility (months):	36	36	3	3
Severance pay (monthly wages):	2	3	2	3
Panel A: Unemployment				
– pre-reform in %	6.54	6.71	8.95	10.80
– post-reform in %	5.94	5.94	5.94	5.94
– change in pp.	0.59	0.76	3.01	4.86
– of which job creation	0.67	0.82	3.36	5.35
– of which job destruction	-0.08	-0.06	-0.36	-0.50
Panel B: Output				
– change in pp.	0.97	1.17	3.84	6.13
Panel C: Output/Worker				
– change in pp.	0.33	0.35	0.52	0.66

Note: This table shows results from a policy simulation exercise conducted based on the baseline model using calibrated (Table 4.8) and estimated (Table 4.9) model parameters. Column 1 compares the pre- and post-reform steady state in the Austrian case, while columns 2 to 4 vary expected time to eligibility ($1/\alpha$) or the size of the mandatory severance payment (ψ) in the pre-reform state.

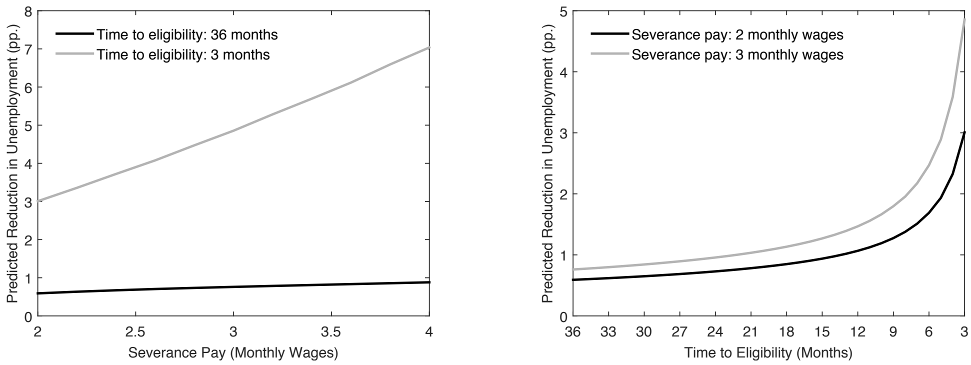
These results suggest an important role for time to eligibility. In Figure 4.17 we look at the relationship between ψ and α and the predicted reduction in equilibrium unemployment in more detail. Figure 4.17a demonstrates that, as long as α is fixed at 1/36, the effect on unemployment never exceeds one percentage point even if severance pay is as high as four monthly wages. This changes markedly if we lower the time to eligibility to three months, where we predict drops in unemployment between 3 and 7 percentage points and an approximately linear relationship. The relationship to time to eligibility, by contrast, is highly nonlinear, as can be seen from Figure 4.17b.[21]

Allowing for temporary employment. While the previous section suggested sizable reform effects on unemployment, our model might not give a completely realistic account of Southern European economies. The reason is that we abstract from temporary employment, which is a prevalent phenomenon in these countries. If firms can decide whether to create regular or temporary jobs there are two margins of adjustment. The concern might be that firms react to a reform simply by substituting temporary with regular jobs, while unemployment is unaffected.

[21] As time to eligibility approaches zero, especially if combined with a high ψ, we also encounter the case where firms do not create any vacancies and an equilibrium is not defined.

Figure 4.17: The effect of varying severance pay or time to eligibility on unemployment

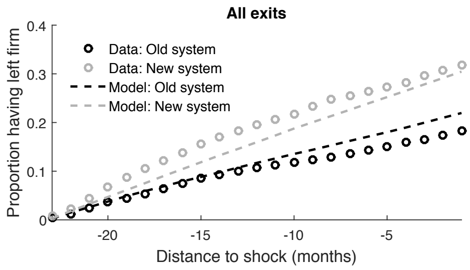
(a) Severance pay (b) Time to eligibility



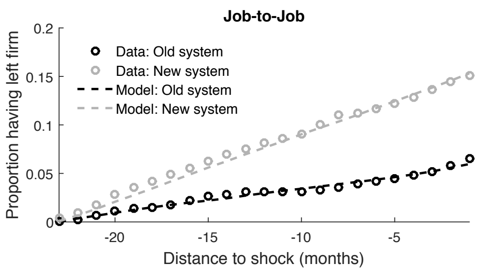
Note: Figure (a) shows the difference between post- and pre-reform equilibrium unemployment for different values of the mandatory severance payment amount, ψ, keeping expected time to eligibility, $1/\alpha$, at 36 or 3. Figure (b) shows the same outcome for different values of expected time to eligibility, keeping the mandatory severance payment amount at 2 or 3.

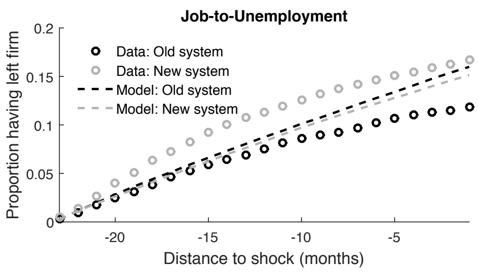
Figure 4.18: Cumulative share of workers leaving into unemployment and to another job, simulated values vs. data (allowing for temporary employment)

(a) Cumulative exit rates (all exits)



(b) Cumulative exit rates (JTJ) (c) Cumulative exit rates (JTU)





Note: The figures compare cumulative exit rates implied by an RDD (see main text for details) on our baseline sample to an RDD based on artificial data generated by the model allowing for temporary jobs using calibrated (Table 4.8) and estimated (Table 4.9) model parameters. Figure (a) shows all exits, while figures (b) and (c) distinguish between JTJ and JTU transitions. Note that we only fit figures (b) and (c) as figure (a) corresponds to the sum of figures (b) and (c).

We address this concern by allowing for temporary employment in our model. We do so by assuming that firms can create vacancies either for regular or temporary jobs. While workers in regular jobs become eligible for severance pay with probability α as

Table 4.12: Simulation results (temporary employment)

	Scenario:			
Time to eligibility (months):	36	36	3	3
Severance pay (monthly wages):	2	3	2	3
Panel A: Share temporary employment				
– pre-reform in %	7.75	7.95	10.04	10.55
– post-reform in %	7.37	7.37	7.37	7.37
– change in pp.	0.38	0.58	2.67	3.18
Panel B: Unemployment				
– pre-reform in %	7.32	7.47	9.17	10.27
– post-reform in %	6.87	6.87	6.87	6.87
– change in pp.	0.45	0.60	2.30	3.40
– of which job creation	0.42	0.47	1.74	2.33
– of which job destruction	0.03	0.13	0.56	1.07
Panel C: Output				
– change in pp.	0.77	0.93	2.78	3.85
Panel D: Output/Worker				
– change in pp.	0.28	0.28	0.24	0.06

Note: This table shows results from a policy simulation exercise conducted based on the model allowing for temporary employment using calibrated (Table 4.8) and estimated (Table 4.9) model parameters. Column 1 compares the pre- and post-reform steady state in the Austrian case, while columns 2 to 4 vary expected time to eligibility ($1/\alpha$) or the size of the mandatory severance payment (ψ) in the pre-reform state.

before, temporary jobs never turn eligible and are dissolved at rate α_t, where α_t is an exogenous probability.[22] Temporary jobs yield lower value, as they are inherently less stable, and workers are less likely to accept offers for temporary jobs. Equilibrium, where firms are indifferent between posting vacancies in either submarket, is attained by fewer firms posting vacancies in the temporary submarket which leads to a higher vacancy filling rate. We describe the full model in Appendix C.

We stick with the calibration of the baseline model summarized in Table 4.8. We set $\alpha_t = 1/36$, consistent with the idea that workers become eligible for severance pay automatically after three years and firms create temporary jobs so as to avoid firing costs. In addition to the moments targeted in the baseline estimation, we also target the fraction of jobs subject to a temporary contract. According to the Micro Census, this is about 4%.

We summarize the estimation results in columns 2 of Table 4.9. The fit of the macro moments is summarized in columns 2 of Table 4.10, while Figure 4.18 demonstrates the fit of the micro moments. Overall, the fit is similar. The model does a decent job in generating temporary employment, while all other moments are in a similar ballpark as

[22] We also estimated an alternative version, where a firm gets the possibility of transforming the job into a permanent (eligible) one once the α_t shock hits. All qualitative results are unaffected.

in the baseline model.

In Table 4.12, we show the results of conducting the same policy simulation exercise as in the baseline case. The broad conclusions regarding unemployment, output, and output per worker are unchanged, even though the effect becomes somewhat weaker. Interestingly, firms seem to react along both margins, reducing temporary employment but overcompensating this by the creation of new jobs so as to reduce unemployment. Thus, it appears that a similar reform can achieve two goals—the reduction of unemployment and the increase in the share of permanent jobs—at the same time.

4.10 Conclusion

In this paper we have looked at a major change in Austrian labor market regulations: the introduction of an occupational pension scheme based on separation payments for private sector workers and the simultaneous abolition of a previous system of severance payment. The new policy brought about two major changes. While only laid-off workers were eligible for severance pay under the old system, both quitters and laid-off workers can keep their accumulated savings on the pension account (and transfer it to a new employer once they have a new job) in the new system. The policy change abolished a discontinuous schedule of severance pay (with jumps at tenure thresholds) in favor of a continuous one (with the balance of the pension account increasing smoothly with employer's monthly contributions). The new policy increases the incentive to quit an employment relation with a distressed firm. By contrast, workers employed under the old system had no such incentive but rather benefited from waiting for their layoff (to receive the severance payment).

This paper uses data from the Austrian social security register (ASSD) to study how the policy change from severance payment to occupational pensions affected job mobility. Using an RD approach, we indeed find that job mobility in distressed firms is substantially higher under the new system compared to the old one. The probability that a worker is still employed at a distressed firm (that is about to experience a mass layoff within the next two years) at the date of the mass layoff is 12.5 percentage points (or around 40 percent) lower then the corresponding probability for workers employed under the old system. Moreover, the difference is almost entirely driven by transitions to new jobs as opposed to transitions into unemployment. Thus, the new system encourages moves from "bad" to "good" firms with potentially important consequences for the allocation of workers and total factor productivity. By comparing workers entering firms shortly before and after the reform, we are able to address potential concerns such as the firms' reaction to their workforce composition and business cycle effects.

To explore the reform's aggregate implications, we propose an equilibrium search model featuring endogenous layoffs and job-to-job mobility. In the model, workers start out as non-eligible and turn eligible with some probability, while firms face productivity (or demand) shocks, changing the likelihood that a worker in a distressed firm will experience a layoff. When the layoff probability is high, a worker who might lose her severance payment optimally waits for the layoff to occur under the old system (rather than search hard for a new job and accept reasonable job offers). Under the new system, a worker—with a separation payment transferred to the new employer—is much more likely to move on to a new and more productive employment relationship.

We estimate the model by Simulated Method of Moments and show that, under realistic parameter values, it generates differences in mobility behavior of similar magnitude as those found in the empirical analysis. The model predicts a moderate decrease in equilibrium unemployment (around 0.6 percentage points) as well as an increase in output per worker, which is driven by quicker reallocation of workers along the job ladder.

Many Southern European economies have systems in place which are more extreme (in terms of time to eligibility and expected size of payment) than the Austrian pre-reform system. Using the parameterized model, we predict in counterfactual simulations that a comparable reform can have sizable effects on unemployment and productivity. This conclusion even holds when allowing for temporary employment, which is widespread in these economies. In this case, the reform is predicted to affect both margins, reducing both unemployment and temporary employment. Thus, we conclude that the Austrian reform might be a potential role model for Southern Europe.

Acknowledgements:

We would like to thank David Autor, Pierre Cahuc, David Dorn, Julien Prat, as well as seminar participants at Bergen, CREST-ENSAE, Edinburgh, OECD, Paris School of Economics, Salzburg, Tuebingen, UCL and Zurich for helpful comments and suggestions.

4.11 Appendix

A Further Robustness Checks

Our empirical strategy is set up as if the date of a mass layoff was as an "exogenous" event. This is obviously not the case as the firm's employment reduction is an endogenous response of the firm to the exogenous event that triggered this response (i.e. unexpectedly lower demand and/or reduced prices for its products or shocks that increase costs). Ideally we would like to know the exact date when a worker learns that her firm was hit by a shock that increases her layoff probability; and the exact date when the worker is informed that she will eventually be fired.

The purpose of this appendix is to document in more detail the size distribution and employment dynamics of mass layoff firms. We also provide related RD evidence that supports the validity of the RD design adopted in our empirical analysis.

One concern might be that the systematically higher outflow due to new-system workers changes the dynamics of the firm size over time in a way that also changes the nature of the employment reduction and thus also the selection of firms in the pre- and the post-reform sample. If this were the case, we should arguably see signs in the firm size distribution in the month preceding the mass layoff. In Table 4.11.1, we inspect the distribution of firm sizes (in the month preceding the mass layoff), comparing the pre- and the post-reform observations. We do not find any systematic differences. Even if there were differences, this would not pose a problem to our strategy if the change in the firm size distribution trends smoothly around the reform threshold. To check this, we measure average firm size in the baseline sample 24, 12 and 1 month before the mass layoff and demonstrate that there is no discontinuity at the time of the reform in Figure 4.11.1.

We might also expect to the see the size of the actual mass layoff affected if more workers exit the firm during the time preceding it. Figures 4.11.2 and 4.11.3 indicate large variation in the size of the mass layoff (while most events seem to be actual plant closures) and even more variation in the change in employment during the two years preceding the event. Still, Figure 4.11.4 suggests that most of the actual change in employment during the last two years is driven by the mass layoff itself (especially in absolute terms), while in relative terms we see that some substitution takes for place for smaller layoffs, meaning that smaller reductions over the last two years are accompanied by larger mass layoffs. Again the crucial thing to verify is that the outcomes trend smoothly around the cutoff: In Figures 4.11.5 and 4.11.6 we confirm that this is the case, with neither the size of the mass layoff (in absolute or relative terms)[23] nor the change in employment in the two

[23] We do observe some spikes in the absolute size of the layoff especially around the year 2000. This is

preceding years (in absolute or relative terms) showing any discontinuity at the time of the reform.

While it might seem surprising that the change in incentives brought about by the reform does not show up in any of the outcomes considered here, the crucial thing to realize is that we are never comparing firms employing solely old- or new-system workers. In fact, as we have seen in Figure 4.5, the difference in work force composition at the firm level actually vanishes at the discontinuity. Thus, we are able to estimate the causal response of the severance pay reform on workers' mobility choices.

Table 4.11.1: Size distribution of mass layoff firms

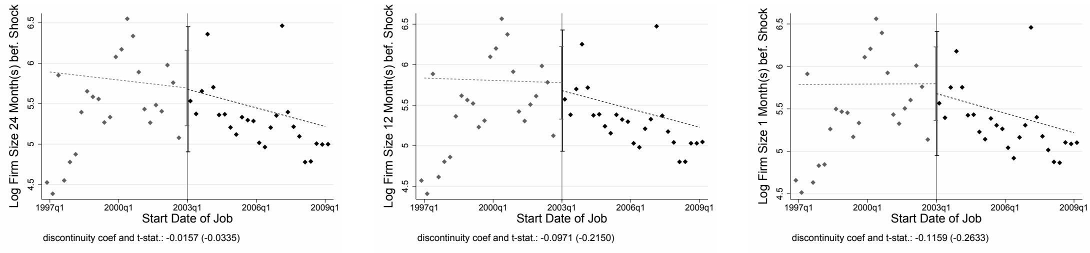
	% Firms in Category	% Workers in Category
Panel A: Pre- and post-observations		
Less than 50 Employees	37.52	13.87
50 – 99 Employees	32.73	18.76
100 – 499 Employees	25.92	32.67
500 – 999 Employees	2.67	15.13
At least 1000 Employees	1.17	19.57
Observations	4198	28099
Panel B: Pre-observations only		
Less than 50 Employees	37.22	13.17
50 – 99 Employees	32.48	18.29
100 – 499 Employees	25.87	31.53
500 – 999 Employees	2.90	16.99
At least 1000 Employees	1.52	20.02
Observations	2238	15600
Panel C: Post-observations only		
Less than 50 Employees	37.03	14.75
50 – 99 Employees	32.80	19.35
100 – 499 Employees	26.72	34.10
500 – 999 Employees	2.63	12.80
At least 1000 Employees	0.83	19.01
Observations	2055	12499

Note: This table shows the distribution of firm sizes in the month preceding the mass layoff in our baseline sample. The first column displays the share of firms in a specific size category, while the second column shows the share of workers in a specific size category. Panel A pools pre- and post-reform observations, while Panel B and C restrict to pre- and post-reform observations, respectively. Even though our baseline results indicate systematically higher outflow by post-reform workers, the firm size distribution at the time of the actual shock does not seem to be affected.

due to single large firm closures.

Figure 4.11.1: Log Firm Size

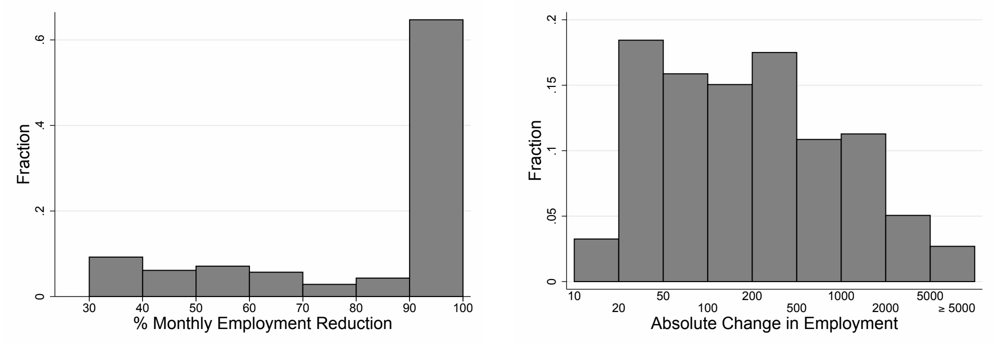
(a) Two years before shock (b) One year before shock (c) One month before shock



Note: The figures show results of RD regressions (based on equation (4.1)). The dependent variable is the log of the firm size 24, 12, and 1 month before the mass layoff measured at the worker level. We give more weight to observations close the cutoff by using a triangular kernel. Inference is based on a bootstrap (1000 replications) clustered at the firm level. The results demonstrate that there are no signs of differential firm size dynamics at the time of the reform.

Figure 4.11.2: Distribution of mass layoffs

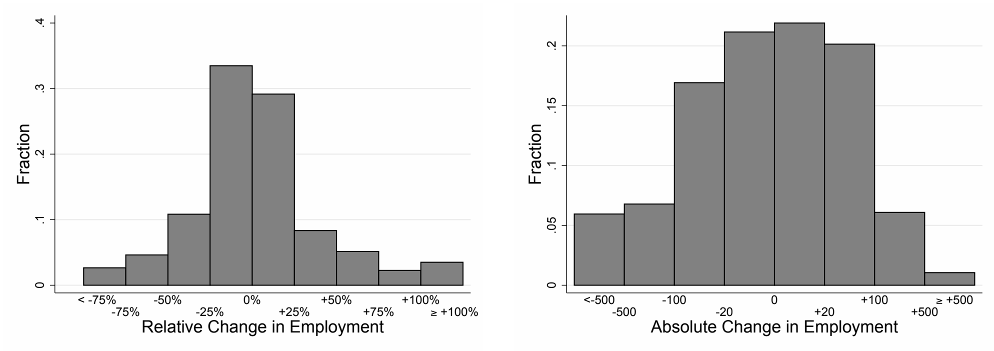
(a) Relative change in employment (b) Absolute change in employment



Note: The figures show histograms of the monthly employment reduction occurring at the time of the mass layoff in the baseline sample. In panel (a) we display the employment reduction relative to the firm size one month before, while panel (b) shows the absolute reduction.

Figure 4.11.3: Relative change in employment 24 months until 1 month before mass layoff

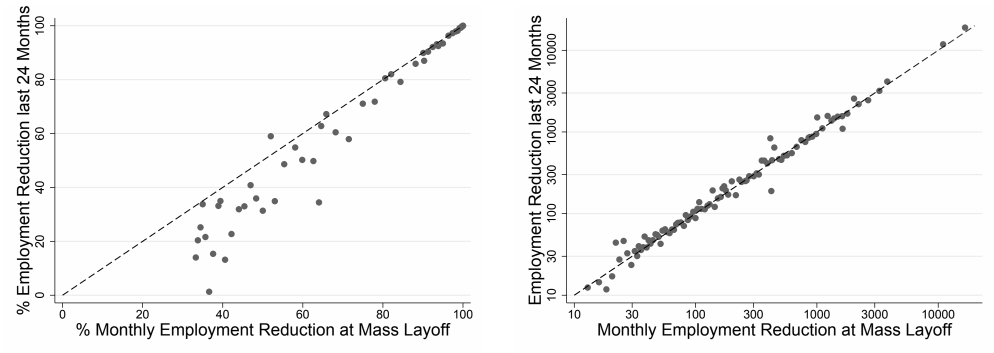
(a) Relative change in employment (b) Absolute change in employment



Note: The figures show histograms of the change in employment occurring two years until one month before the mass layoff in the baseline sample. In panel (a) we display the change in employment relative to the firm size one month before, while panel (b) shows the absolute change.

Figure 4.11.4: Change in last two years against change in last month

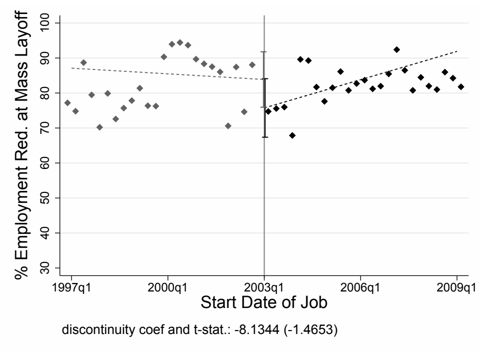
(a) Month -24 until Month 0 vs. Month -1 until Month 0 (relative) (b) Month -24 until Month 0 vs. Month -1 until Month 0 (absolute)



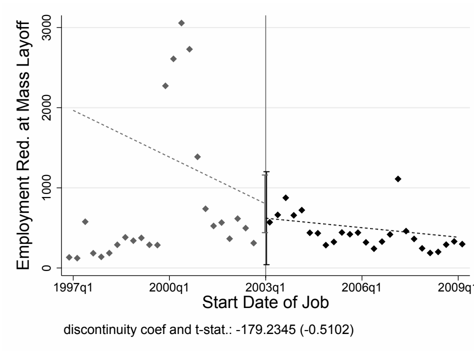
Note: The figures show the relationship between the change in employment occurring during the last two years and the last month preceding the mass layoff, either in relative terms (panel (a)) or in absolute terms (panel (b)). The dots indicate averages within 100 quantiles of the variable on the horizontal axis, respectively. The dashed line denotes the 45° line. The results indicate that most of the reduction during the last two years before the mass layoff are driven by the change due to the actual mass layoff. In relative terms, some substitution appears to occur, as firms with smaller reductions during the time preceding the mass layoff experience somewhat larger mass layoffs.

Figure 4.11.5: Average layoff size by start date

(a) Relative



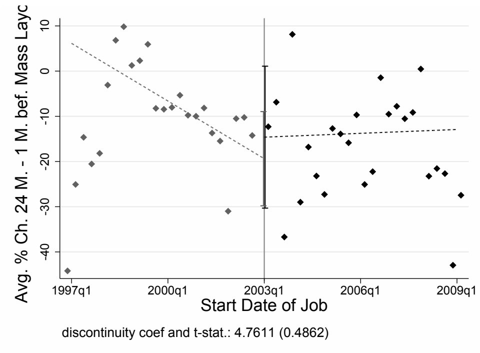
(b) Absolute



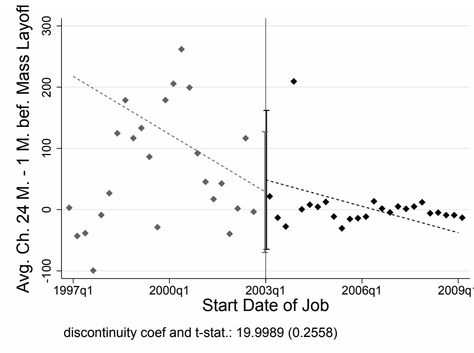
Note: The figures show results of RD regressions (based on equation (4.1)). The dependent variable is the monthly employment reduction at the time of the mass layoff relative to the firm size one month before (panel (a)) and in absolute terms (panel (b)) measured at the worker level. We give more weight to observations close the cutoff by using a triangular kernel. Inference is based on a bootstrap (1000 replications) clustered at the firm level. The results demonstrate that there are no signs of differences in shock size at the time of the reform.

Figure 4.11.6: Change in employment 24 months before mass layoff until 1 month before mass layoff

(a) Relative change



(b) Absolute change



Note: The figures show results of RD regressions (based on equation (4.1)). The dependent variable is the employment reduction between two years and one month before the mass layoff, relative to employment two years before (panel (a)) and in absolute terms (panel (b)) measured at the worker level. We give more weight to observations close the cutoff by using a triangular kernel. Inference is based on a bootstrap (1000 replications) clustered at the firm level. The results demonstrate that there are no signs of differences in shock size at the time of the reform.

B Baseline Model

Steady State

The value of a firm employing an eligible worker, $J_1(p)$, is given by (throughout, primes denote next-period values)

$$J_1(p) = p - w_1(p) + \delta\lambda(-\psi) + \delta(1 - \chi f \bar{\mu}_1(p) - \lambda) \int_{\underline{p}}^{\overline{p}} \gamma_1(p')(-\psi) + (1 - \gamma_1(p'))J_1(p')\, dF(p'|p),$$

where $w_1(p)$ is the bargained wage of an eligible worker given productivity p. Firms currently earn $p - w_1(p)$. With probability $(1 - \chi f \mu_1(p) - \lambda)$, the match persists and a new productivity realization p' is drawn. Upon observing this draw, firms can either shut down and pay ψ or continue to produce, earning $J_1(p')$.

The value of a firm employing a non-eligible worker, $J_0(p)$, satisfies

$$\begin{aligned} J_0(p) = p - w_0(p) + \delta(1 - \chi f \bar{\mu}_0(p) - \lambda) \int_{\underline{p}}^{\overline{p}} & \alpha \left(\gamma_1(p')(-\psi) + (1 - \gamma_1(p'))J_1(p')\right) \\ & + (1 - \alpha)(1 - \gamma_0(p'))J_0(p')\, dF(p'|p). \end{aligned}$$

Given that the match persists, workers become eligible with probability α. In this case, the firm has to pay ψ if shutting down and has continuation value $J_1(p')$ else. If the worker does not become eligible, the firm does not have to make a transfer in case of a layoff, while it continues with $J_0(p')$ if not.

The value of an eligible worker, $W_1(p)$, is given by

$$\begin{aligned} W_1(p) = {} & w_1(p) + \delta\lambda(U + \psi) \\ & + \delta\chi f \int_{\underline{p}}^{\overline{p}} \alpha\mu_1^1(p, p^o)W_1(p^o) + (1 - \alpha)\mu_1^0(p, p^o)W_0(p^o)\, dG(p^o) \\ & + \delta(1 - \chi f \bar{\mu}_1(p) - \lambda) \int_{\underline{p}}^{\overline{p}} \gamma_1(p')(U + \psi) + (1 - \gamma_1(p'))W_1(p')dF(p'|p), \end{aligned}$$

where U is the value when unemployed. A worker currently earns $w_1(p)$, with probability λ an exogenous separation occurs, and with probability χf an outside offer with productivity p^o is obtained. If the workers does not receive an outside offer or turns it down, the worker becomes unemployed and receives ψ if the firm is shut down, while receiving continuation value $W_1(p')$ otherwise.

The value of a non-eligible worker, $W_0(p)$, is given by

$$
\begin{aligned}
W_0(p) = w_0(p) + \delta\lambda U \\
&+ \delta\chi f \int_{\underline{p}}^{\overline{p}} \alpha\mu_0^1(p,p^o)W_1(p^o) + (1-\alpha)\mu_0^0(p,p^o)W_0(p^o)\, dG(p^o) \\
&+ \delta(1-\chi f\bar{\mu}_0(p) - \lambda) \int_{\underline{p}}^{\overline{p}} \alpha\left[\gamma_1(p')(U+\psi) + (1-\gamma_1(p'))W_1(p')\right] \\
&\qquad + (1-\alpha)\left[\gamma_0(p')U + (1-\gamma_0(p'))W_0(p')\right] dF(p'|p).
\end{aligned}
$$

Note that neither an eligible nor a non-eligible worker will accept an offer that results in an immediate layoff $\gamma_i(p^o) = 1$ due to the bargaining assumption. Hence, we do not have to account for this possibility.

The value when unemployed reads:

$$
U = b + \delta f \int_{\underline{p}}^{\overline{p}} \alpha\mu_u^1(p^o)W_1(p^o) + (1-\alpha)\mu_u^0(p^o)W_0(p^o)\, dG(p^o) + \delta(1-f\bar{\mu}_u)U
$$

We assume that firms have to pay ψ to an eligible worker if bargaining breaks down. As the value of a vacancy is 0, firms' outside value is $0-\psi = -\psi$. Workers' outside value is $U+\psi$. The common surplus, $S_1(p)$ is then given by

$$
S_1(p) = (W_1(p) - (U+\psi)) + (J_1(p) - (-\psi)) = W_1(p) - U + J_1(p).
$$

Nash bargaining implies

$$
W_1(p) - (U+\psi) = \beta S_1(p) \;\text{ and }\; J_1(p) + \psi = (1-\beta)S_1(p),
$$

where β denotes workers' bargaining power. Similarly, the surplus if the worker is not eligible, $S_0(p)$, is given by

$$
S_0(p) = W_0(p) - U + J_0(p)
$$

and

$$
W_0(p) - U = \beta S_0(p) \;\text{ and }\; J_0(p) = (1-\beta)S_0(p).
$$

There is no need to solve explicitly for the values of workers and firms, since all equilibrium objects can be characterized as functions of the surplus functions. Combining the firm's and worker's value functions and using the bargaining assumption, we find

$$S_1(p) = p - b + \delta f \int_{\underline{p}}^{\overline{p}} \alpha(\chi\mu_1^1(p,p^o) - \mu_u^1(p^o))(\beta S_1(p^o) + \psi)$$
$$+ (1-\alpha)(\chi\mu_1^0(p,p^o) - \mu_u^0(p^o))\beta S_0(p^o)\, dG(p^o)$$
$$+ \delta(1-\lambda-\chi f\bar{\mu}_1(p)) \int_{\underline{p}}^{\overline{p}} (1-\gamma_1(p'))S_1(p')dF(p'|p) \quad (4.7)$$

and

$$S_0(p) = p - b + \delta f \int_{\underline{p}}^{\overline{p}} \alpha(\chi\mu_0^1(p,p^o) - \mu_u^1(p^o))(\beta S_1(p^o) + \psi)$$
$$+ (1-\alpha)(\chi\mu_0^0(p,p^o) - \mu_u^0(p^o))\beta S_0(p^o)\, dG(p^o)$$
$$+ \delta(1-\lambda-\chi f\bar{\mu}_0(p)) \int_{\underline{p}}^{\overline{p}} \alpha(1-\gamma_1(p'))S_1(p') + (1-\alpha)(1-\gamma_0(p'))S_0(p')dF(p'|p). \quad (4.8)$$

Surplus Functions in Transition

To account for transition from the old to the new steady state, fix a value of θ and hence of f. The surplus function of the new-system workers is not affected and still satisfies equations (4.3) and (4.2) for a given f (note that both equations coincide for $\psi = 0$). Call it $\tilde{S}^{new}$, where tilde denotes values in transition in what follows. The old-system workers take into account that any new match will be subject to the new system. Hence, their surplus functions satisfy

$$\tilde{S}_1^{old}(p) = p - b + \delta f \int_{\underline{p}}^{\overline{p}} (\chi\tilde{\mu}_1^{old}(p,p^o) - \tilde{\mu}_u(p^o))\beta\tilde{S}^{new}(p^o)\, dG(p^o)$$
$$+ \delta(1-\lambda-\chi f\bar{\tilde{\mu}}_1^{old}(p)) \int_{\underline{p}}^{\overline{p}} (1-\tilde{\gamma}_1^{old}(p'))\tilde{S}_1^{old}(p')dF(p'|p) \quad (4.9)$$

and

$$\tilde{S}_0^{old}(p) = p - b + \delta f \int_{\underline{p}}^{\overline{p}} (\chi\tilde{\mu}_0^{old}(p,p^o) - \tilde{\mu}_u(p^o))\beta\tilde{S}^{new}(p^o)\, dG(p^o)$$
$$+ \delta(1-\lambda-\chi f\bar{\tilde{\mu}}_0^{old}(p)) \int_{\underline{p}}^{\overline{p}} \alpha(1-\tilde{\gamma}_1^{old}(p'))\tilde{S}_1^{old}(p')$$
$$+ (1-\alpha)(1-\tilde{\gamma}_0^{old}(p'))\tilde{S}_0^{old}(p')dF(p'|p). \quad (4.10)$$

Optimal firm closures follow as

$$\tilde{\gamma}_0^{old}(p) = \mathbb{1}\left\{\tilde{S}_0^{old}(p) < 0\right\}$$
$$\tilde{\gamma}_1^{old}(p) = \mathbb{1}\left\{\tilde{S}_1^{old}(p) < 0\right\}$$
$$\tilde{\gamma}^{new}(p) = \mathbb{1}\left\{\tilde{S}^{new}(p) < 0\right\},$$

while workers' acceptance rules are given by

$$\begin{aligned}\tilde{\mu}_0^{old}(p,p^o) =& \mathbb{1}\Bigg\{\beta\tilde{S}^{new}(p^o) > \alpha\psi + \int_{\underline{p}}^{\overline{p}} \alpha(1-\tilde{\gamma}_1^{old}(p'))\beta\tilde{S}_1^{old}(p') \\ & \qquad + (1-\alpha)(1-\tilde{\gamma}_0^{old}(p'))\beta\tilde{S}_0^{old}(p')\,dF(p'|p)\Bigg\} \\ \tilde{\mu}_1^{old}(p,p^o) =& \mathbb{1}\left\{\beta\tilde{S}^{new}(p^o) > \psi + \int_{\underline{p}}^{\overline{p}} (1-\tilde{\gamma}_1^{old}(p'))\beta\tilde{S}_1^{old}(p')\,dF(p'|p)\right\} \\ \tilde{\mu}^{new}(p,p^o) =& \mathbb{1}\left\{\beta\tilde{S}^{new}(p^o) > \int_{\underline{p}}^{\overline{p}} (1-\tilde{\gamma}^{new}(p'))\beta\tilde{S}^{new}(p')\,dF(p'|p)\right\}.\end{aligned}$$

C Allowing for Temporary Jobs

Environment

The environment in the baseline model is adapted by adding the possibility to create temporary jobs. We assume that temporary jobs are fixed-term. That is, with exogenous rate α_t, temporary matches are dissolved at the beginning of the period.

Endogenous Firm and Worker Decisions

We denote by $\gamma_i(p) \in \{0,1,t\}$ the endogenous firm closure decision given productivity p and eligibity status i of the worker, where t now indicates a temporary job. Moreover, let $\mu_i^j(p,p^o)$ indicate the endogenous decision of a worker with current eligibility status $i \in \{0,1,t\}$ employed by a firm facing productivity p to accept an outside offer by a firm facing productivity p^o where she will have eligibility status $j \in \{0,1,t\}$. The overall probability that a worker accepts an outside offer for a *regular* job given productivity p and eligibility status i is given by

$$\bar{\mu}_i(p) = \int_{\underline{p}}^{\overline{p}} \alpha\mu_i^1(p,p^o) + (1-\alpha)\mu_i^0(p,p^o)\,dG(p^o).$$

Similarly, denote by $\mu_u^j(p^o)$ the endogenous decision by an unemployed worker to accept an offer by a firm facing productivity p^o where she will have eligibility status $j \in \{0, 1, t\}$ and define the overall probability of accepting a regular job as

$$\bar{\mu}_u(p) = \int_{\underline{p}}^{\overline{p}} \alpha \mu_u^1(p^o) + (1-\alpha)\mu_u^0(p^o)\, dG(p^o).$$

Bellman Equations

The value of a firm with an eligible worker, $J_1(p)$, is given by

$$\begin{aligned} J_1(p) = p - w_1(p) + \delta\lambda(-\psi) + \\ \delta(1 - \chi f_r \bar{\mu}_1(p) - \chi f_t \mu_1^t(p) - \lambda) \int_{\underline{p}}^{\overline{p}} \gamma_1(p')(-\psi) + (1 - \gamma_1(p'))J_1(p') dF(p'|p), \end{aligned}$$

where f_r and f_t denote the probability that a worker meets a firm offering a regular or temporary job, respectively.

The value of a firm with a non-eligible worker, $J_0(p)$, satisfies

$$\begin{aligned} J_0(p) = p - w_0(p) + \\ \delta(1 - \chi f_r \bar{\mu}_0(p) - \chi f_t \mu_0^t(p) - \lambda) \int_{\underline{p}}^{\overline{p}} \alpha \left[\gamma_1(p')(-\psi) + (1 - \gamma_1(p'))J_1(p')\right] \\ + (1-\alpha)(1 - \gamma_0(p'))J_0(p') dF(p'|p), \end{aligned}$$

while the value of a temporary job to a firm, $J_t(p)$, is given by

$$J_t(p) = p - w_t(p) + \delta(1 - \chi f_r \bar{\mu}_t(p) - \chi f_t \mu_t^t(p) - \lambda) \int_{\underline{p}}^{\overline{p}} (1 - \alpha_t)(1 - \gamma_t(p'))J_t(p') dF(p'|p).$$

In addition to exogenous separations with rate λ and job-to-job transitions, a temporary job is destroyed at the beginning of a period at rate α_t.

The value of an eligible worker, $W_1(p)$, is given by

$$
\begin{aligned}
W_1(p) = w_1(p) &+ \delta\lambda(U+\psi) \\
&+ \delta\chi f_r \int_{\underline{p}}^{\overline{p}} \alpha\mu_1^1(p,p^o)W_1(p^o) + (1-\alpha)\mu_1^0(p,p^o)W_0(p^o)\, dG(p^o) \\
&+ \delta\chi f_t \int_{\underline{p}}^{\overline{p}} \mu_1^t(p,p^o)W_t(p^o)\, dG(p^o) \\
&+ \delta(1-\chi f_r\bar{\mu}_1(p) - \chi f_t \mu_t^1(p) - \lambda) \int_{\underline{p}}^{\overline{p}} \gamma_1(p')(U+\psi) + (1-\gamma_1(p'))W_1(p') dF(p'|p),
\end{aligned}
$$

where U is the value when unemployed, $G(p^o)$ is the distribution of outside offers p^o (i.e. the unconditional distribution of p), and $\gamma_1(p)$ takes the value 1 if a firm with an eligible worker is shut down given p and zero otherwise. A worker currently earns $w_1(p)$, with probability λ an exogenous separation occurs, and with probability χf an outside offer with productivity p^o is obtained. If the workers does not receive an outside offer or turns it down, the worker becomes unemployed and receives ψ if the firm is shut down, while receiving continuation value $W_1(p')$ otherwise.

The value of a non-eligible worker, $W_0(p)$, is given by

$$
\begin{aligned}
W_0(p) = w_0(p) &+ \delta\lambda U \\
&+ \delta\chi f_r \int_{\underline{p}}^{\overline{p}} \alpha\mu_0^1(p,p^o)W_1(p^o) + (1-\alpha)\mu_0^0(p,p^o)W_0(p^o)\, dG(p^o) \\
&+ \delta\chi f_t \int_{\underline{p}}^{\overline{p}} \mu_0^t(p,p^o)W_t(p^o)\, dG(p^o) \\
&+ \delta(1-\chi f_r\bar{\mu}_0(p) - \chi f_t \mu_t^0(p) - \lambda) \int_{\underline{p}}^{\overline{p}} \alpha\left[\gamma_1(p')(U+\psi) + (1-\gamma_1(p'))W_1(p')\right] \\
&\qquad + (1-\alpha)\left[\gamma_0(p')U + (1-\gamma_0(p'))W_0(p')\right] dF(p'|p).
\end{aligned}
$$

The value of a temporary worker, $W_t(p)$, is given by

$$
\begin{aligned}
W_t(p) = w_t(p) &+ \delta\lambda U \\
&+ \delta\chi f_r \int_{\underline{p}}^{\overline{p}} \alpha\mu_t^1(p,p^o)W_1(p^o) + (1-\alpha)\mu_t^0(p,p^o)W_0(p^o)\, dG(p^o) \\
&+ \delta\chi f_t \int_{\underline{p}}^{\overline{p}} \mu_t^t(p,p^o)W_t(p^o)\, dG(p^o) \\
&+\delta(1-\lambda-\chi f_r\bar{\mu}_t(p) - \chi f_t \mu_t^t(p)) \int_{\underline{p}}^{\overline{p}} \alpha_t U + (1-\alpha_t)\left[\gamma_t(p')U + (1-\gamma_t(p'))W_t(p')\right] dF(p'|p).
\end{aligned}
$$

The value when unemployed reads:

$$U = b + \delta f_r \int_{\underline{p}}^{\overline{p}} \alpha \mu_u^1(p, p^o) W_1(p^o) + (1-\alpha)\mu_u^0(p, p^o) W_0(p^o)\, dG(p^o)$$
$$+ \delta f_t \int_{\underline{p}}^{\overline{p}} \mu_u^t(p^o) W_t(p^o)\, dG(p^o) + \delta(1 - f_r \bar{\mu}_u - f_t \mu_u^t) U$$

The surplus functions satisfy:

$$S_1(p) = (W_1(p) - (U + \psi)) + (J_1(p) - (-\psi)) = W_1(p) - U + J_1(p).$$

$$W_1(p) - (U + \psi) = \beta S_1(p) \text{ and } J_1(p) + \psi = (1-\beta) S_1(p),$$

$$S_0(p) = W_0(p) - U + J_0(p)$$

$$W_0(p) - U = \beta S_0(p) \text{ and } J_0(p) = (1-\beta) S_0(p).$$

$$S_t(p) = W_t(p) - U + J_t(p)$$

$$W_t(p) - U = \beta S_t(p) \text{ and } J_t(p) = (1-\beta) S_t(p).$$

Combining the firm's and worker's value functions and using the bargaining assumption, we find

$$S_1(p) = p - b + \delta f_r O_1(p) + \delta f_t O_1^t(p)$$
$$+ \delta(1 - \chi f_r \bar{\mu}_1(p) - \chi f_t \mu_t^1(p) - \lambda) \int_{\underline{p}}^{\overline{p}} (1 - \gamma_1(p')) S_1(p') dF(p'|p), \quad (4.11)$$

$$S_0(p) = p - b + \delta f_r O_0(p) + \delta f_t O_0^t(p)$$
$$+ \delta(1 - \chi f_r \bar{\mu}_0(p) - \chi f_t \mu_0^t(p) - \lambda) \int_{\underline{p}}^{\overline{p}} \alpha(1 - \gamma_1(p')) S_1(p')$$
$$+ (1-\alpha)(1 - \gamma_0(p')) S_0(p') dF(p'|p), \quad (4.12)$$

and

$$S_t(p) = p - b + \delta f_r O_t(p) + \delta f_t O_t^t(p)$$
$$+ \delta(1 - \chi f_r \bar{\mu}_t(p) - \chi f_t \mu_t^t(p) - \lambda) \int_{\underline{p}}^{\overline{p}} (1 - \alpha_t)(1 - \gamma_t(p')) S_t(p') dF(p'|p). \quad (4.13)$$

where

$$O_i(p) = \int_{\underline{p}}^{\overline{p}} \alpha(\chi\mu_i^1(p,p^o) - \mu_u^1(p^o))(\beta S_1(p^o) + \psi) + (1-\alpha)(\chi\mu_i^0(p,p^o) - \mu_u^0(p^o))\beta S_0(p^o)\, dG(p^o),$$

for $i \in \{0, 1, t\}$, denotes the option value due to a potential transition to a regular job and

$$O_i^t(p) = \int_{\underline{p}}^{\overline{p}} (\chi\mu_i^t(p,p^o) - \mu_u^t(p^o))\beta S_t(p^o)\, dG(p^o)$$

for $i \in \{0, 1, t\}$, denotes the option value due to a potential transition to a temporary job.

$\mu_u(p^o)$ takes the value 1 if an unemployed accepts an offer with initial productivity p^o and the decision rules to shut down the firm, γ_0,γ_1, and γ_t, are given by

$$\gamma_i = \mathbb{1}\{S_i < 0\} \quad \text{for } i \in \{0, 1, t\}\,.$$

That is, due to the bargaining assumption, it does not matter whether we think of a lay-off as firm- or worker-induced, since both parties choose to shut down the firm as soon as the joint surplus falls below zero.

The decision rules of the workers are given by

$$\mu_i^j(p,p^o) = \mathbb{1}[V_j^o(p^o) > V_i^s(p)] \quad \text{for } i \in \{0, 1, t, u\} \text{ and } j \in \{0, 1, t\}\,,$$

where V_i^o and V_j^s denote, respectively, the workers' value of staying with i and the offer j. The value of the offer satisfies

$$\begin{aligned}
V_0^o(p^o) &= \beta S_0(p^o)\\
V_t^o(p^o) &= \beta S_t(p^o)\\
V_1^o(p^o) &= \beta S_1(p^o) + \psi,
\end{aligned}$$

while the value of staying can be written

$$\begin{aligned}
V_0^s(p) &= \alpha\psi + \int_{\underline{p}}^{\overline{p}} \alpha\left[(1-\gamma_1(p'))\beta S_1(p')\right] + (1-\alpha)(1-\gamma_0(p'))\beta S_0(p')\, dF(p'|p)\\
V_t^s(p) &= \int_{\underline{p}}^{\overline{p}} (1-\alpha_t)(1-\gamma_t(p'))\beta S_t(p')\, dF(p'|p)\\
V_1^s(p) &= \psi + \int_{\underline{p}}^{\overline{p}} (1-\gamma_1(p'))\beta S_1(p')\, dF(p'|p)\\
V_u^s(p) &= 0.
\end{aligned}$$

Stationary Employment Distribution

Since there is a unit measure of workers, the unemployment rate satisfies $u = \int_{\underline{p}}^{\overline{p}} n_0(p) + n_1(p) + n_t(p)\, dp$.

$n_0(p)$, $n_1(p)$, and $n_t(p)$ satisfy the following properties: For all $p' \in \left[\underline{p}, \overline{p}\right]$,

$$n_0(p') = (1-\gamma_0(p'))(1-\alpha)\int_{\underline{p}}^{\overline{p}}(1-\chi f_r\bar{\mu}_0(p) - \chi f_t\mu_0^t(p) - \lambda)n_0(p)f(p'|p)\,dp + (1-\alpha)f_r u\mu_u^0(p')g(p') + (1-\alpha)\chi f_r\int_{\underline{p}}^{\overline{p}}(n_0(p)\mu_0^0(p,p') + n_1(p)\mu_1^0(p,p') + n_t(p)\mu_t^0(p,p'))g(p')dp, \quad (4.14)$$

$$n_1(p') = (1-\gamma_1(p'))\int_{\underline{p}}^{\overline{p}}(1-\chi f_r\bar{\mu}_1(p) - \chi f_t\mu_t^1(p) - \lambda)n_1(p)f(p'|p)\,dp + \alpha f_r u\mu_u^1(p')g(p') + \alpha\chi f_r\int_{\underline{p}}^{\overline{p}}(n_0(p)\mu_0^1(p,p') + n_1(p)\mu_1^1(p,p') + n_t(p)\mu_t^1(p,p'))g(p')dp + \alpha(1-\gamma_1(p'))\int_{\underline{p}}^{\overline{p}}(1-\chi f_r\bar{\mu}_0(p) - \chi f_t\mu_0^t(p) - \lambda)n_0(p)f(p'|p)\,dp, \quad (4.15)$$

and

$$n_t(p') = (1-\alpha_t)(1-\gamma_t(p'))\int_{\underline{p}}^{\overline{p}}(1-\chi f_r\bar{\mu}_t(p) - \chi f_t\mu_t^t(p) - \lambda)n_t(p)f(p'|p)\,dp + f_t u\mu_u^t(p')g(p') + \chi f_t\int_{\underline{p}}^{\overline{p}}(n_0(p)\mu_u^t(p,p') + n_1(p)\mu_1^t(p,p') + n_t(p)\mu_t^t(p,p'))g(p')dp. \quad (4.16)$$

Zero Profit Condition

We assume that there are two submarkets, one for permanent and one for temporary jobs. Denote by v_r and v_t the number of vacancies for permanent and temporary jobs, respectively. To keep things simple, we assume that the effective number of job seekers, $u + \chi(1-u)$, always searches in both markets.

The number of meetings between a vacant firm and a potential employee in submarket $i \in \{r, t\}$ is then given by the meeting function

$$m_i = m(u + \chi(1-u), v_i).$$

Define labor market tightness $\theta_i \equiv \frac{v_i}{u+\chi(1-u)}$. Assuming that $m(u + \chi(1-u), v)$ satisfies constant returns to scale, we can write for the probability that a vacant firm meets a worker in submarket i, q_i,

$$q_i = \frac{m_i}{v_i} = m(\theta_i^{-1}, 1) \equiv q(\theta_i) \text{ with } q'(\theta_i) < 0.$$

The probability of meeting an unemployed person is given by $q_i u/(u + \chi(1-u))$, while the probability of meeting an employed person is given by $q_i \chi(1-u)/(u+\chi(1-u))$. The probability that an unemployed person meets a firm in submarket i, f_i, can be written

$$f_i = \frac{m_i}{u + \chi(1-u)} = m(1, \theta_i) \equiv f(\theta_i) \text{ with } f'(\theta_i) > 0,$$

while the probability that an employed person meets a firm is given by χf_i.

Denote by $a_i(p^o)$ the probability that an offer by a firm with initial productivity p^o and status $i \in \{0, 1, t\}$ is accepted. It is given by

$$a_i(p^o) = \frac{u}{u + \chi(1-u)} \cdot \mu_u^i(p^o) + \frac{\chi(1-u)}{u + \chi(1-u)} \cdot \frac{\int_{\underline{p}}^{\overline{p}} n_0(p)\mu_0^i(p, p^o) + n_1(p)\mu_1^i(p, p^o) + n_t(p)\mu_t^i(p, p^o) dp}{1-u}.$$

The expected value of a vacancy in submarket t, V_t, then satisfies

$$V_t = -c + \delta q(\theta_t) \int_{\underline{p}}^{\overline{p}} a_t(p^o)(1-\beta)S_t(p^o)\, dG(p^o),$$

while the value of a vacancy in submarket r, V_r, satisfies

$$V_0 = -c + \delta q(\theta_r) \int_{\underline{p}}^{\overline{p}} \alpha a_1(p^o)((1-\beta)S_1(p^o) - \psi) + (1-\alpha)a_0(p^o)(1-\beta)S_0(p^o)\, dG(p^o).$$

A vacant firm pays hiring costs c every period. With probability q_i the firm meets a potential worker and draws initial productivity p^o from the distribution $G(p^o)$. If the offer is accepted, the firm can start producing in the subsequent period, yielding value J_i.

Due to free entry, a vacancy has to yield zero expected profits, i.e.

$$V_i = 0 \text{ for } i \in \{r, t\}, \tag{4.17}$$

also implying that firms are indifferent between creating temporary and permanent jobs in equilibrium.

Equilibrium

Definition 4.2. *An equilibrium is given by functions* $\{n_0(p), n_1(p), n_t(p)\}$*, values* $\{S_0(p), S_1(p), S_t(p)\}$ *and labor market tightness* $\{\theta_r, \theta_t\}$ *such that*

1. *$\{S_0(p), S_1(p), S_t(p)\}$ solve the recursive equations (4.11), (4.12), and (4.13);*

2. *$\{n_0(p), n_1(p), n_t(p)\}$ solve the recursive equations (4.14), (4.15), and (4.16);*

3. *$\{\theta_r, \theta_t\}$ solve the zero-profit condition (4.17).*

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